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Forecasting Motor Vehicle Ownership and Energy Demand Considering Electric Vehicle Penetration

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Abstract: Given the increasing environmental concerns and energy consumption, the transformation of the new energy vehicle industry is a key link in the innovation of the energy structure. The shift from traditional fossil fuels to clean energy encompasses various dimensions such as technological innovation, policy support, infrastructure development, and changes in consumer preferences. Predicting the future ownership of electric vehicles (EVs) and then estimating the energy demand for transportation is a pressing issue in the field of new energy. This study starts from dimensions such as cost, technology, environment, and consumer preferences, deeply explores the influencing factors on the ownership of EVs, analyzes the mechanisms of various factors on the development of EVs, establishes a predictive model for the ownership of motor vehicles considering the penetration of electric vehicles based on system dynamics, and then simulates the future annual trends in EV and conventional vehicle (CV) ownership under different scenarios based on the intensity of government funding. Using energy consumption formulas under different power modes, this study quantifies the electrification energy demand for transportation flows as fleet structure changes. The results indicate that under current policy implementation, the domestic ownership of EVs and CVs is projected to grow to 172.437 million and 433.362 million, respectively, by 2035, with the proportion of EV ownership in vehicles and energy consumption per thousand vehicles at 28.46% and 566,781 J·km^{-1}, respectively. By increasing the technical and environmental factors by 40% and extending the preferential policies for purchasing new energy vehicles, domestic EV ownership is expected to increase to 201.276 million by 2035. This study provides data support for the government to formulate promotional policies and can also offer data support for the development of basic charging infrastructure.

Keywords: motor vehicle ownership; system dynamics; energy demand forecast

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1. Introduction

Energy is the key material foundation supporting national economic development, while transportation is a pillar sustaining the growth of the national economy. The development of transportation and that of energy supply are closely intertwined. The transportation industry is one of the three major high-carbon emission sectors in China, and achieving carbon neutrality in the transportation system is crucial for realizing the country's "dual carbon" goals [1]. In a report by the 20th National Congress of the Communist Party of China, it was emphasized to gradually optimize and adjust the transportation structure to achieve green and low-carbon development goals. As a major pillar in the development process, the energy industry needs to advance continuously with high quality and focus on the future direction of transportation—the efficient utilization of clean energy, based on a comprehensive balance between the national economy and overall social development. The "National Comprehensive Three-dimensional Transportation Network Plan Outline"

proposes the implementation needs for promoting the low carbonization of the transportation energy system and emphasizes the optimization and adjustment of the transportation structure. It points out the two major development trends in low carbonization in the energy consumption structure and transportation modes [2].

The transportation industry in China is massive, with a huge total energy consumption, and during the "13th Five-Year Plan" period, the total energy consumption in the transportation industry increased by as much as 17.7%. According to data from the 2023 China Statistical Yearbook, in 2022, the total energy consumption of the transportation industry in China reached a staggering 4.3935×10^8 tons of standard coal equivalent (tce), accounting for approximately 8.35% of the total energy consumption throughout the whole of society. Due to the significant proportion of road transportation in the total transport volume, gasoline consumption in the transportation industry accounts for over 43% of the total fuel consumption, while electricity consumption is only around 2%. Promoting deep integration and high-quality development between the transportation and energy sectors is a complex and long-term systematic task. Vehicle emissions are also restricted by appropriate regulations, which is one of the reasons for the increasing use of electric vehicles. Several European cities have already introduced low-emission zones, where the use of vehicles is subject to mandatory conditions, though the focus is primarily on new heavy-duty (HD) vehicles and buses [3]. Currently, China's emission standards follow the second phase of the National Stage VI Emission Standards, which impose stricter requirements on the emission of pollutants from vehicle exhausts. An important feature of future transportation energy is a significant increase in electrification. Electric vehicles have the potential to reduce exhaust emissions and fuel consumption, but their true environmental benefits depend on the source of electricity used for charging. If the electricity comes from renewable sources rather than coal, electric vehicles could effectively reduce CO_2 emissions and curb the growth of greenhouse gasses. One study [4] uses the principles of the EN 16 258: 2012 [5] standard to calculate energy consumption and greenhouse gas emissions, accurately assessing electric vehicles' contribution to carbon reduction. Road transportation infrastructure is large in scale, with long routes and extensive land use, providing natural resources for the utilization of new energy. Electric vehicles and other transportation tools will become important components of large-scale distributed energy storage in the future. The distribution and load characteristics of road transportation systems are particularly important for the development and utilization of new energy. Currently, the scale of road transportation continues to expand, with significant growth in both transportation demand and energy consumption. Driven by policy guidance and market demand, according to statistics released by the Ministry of Public Security, the number of new energy vehicles is growing rapidly. By the end of 2023, the total number had increased to 20.41 million, accounting for 6.07% of the total number of vehicles in the country. However, despite this explosive growth in the production and sales of new energy vehicles in China, their development is still in its early stages. They face challenges such as an inadequate institutional framework, heavy government subsidies, issues with low-temperature charging, and the fact that new energy vehicles are not yet widely used compared to traditional vehicles. Predicting the future number of new energy vehicles and calculating the energy demand for traffic flow are important issues in the field of new energy today.

In the field of forecasting automobile ownership, scholars mainly focus on two types of methods: time series analysis models and regression analysis models. Tomas et al. [6] established a dynamic model for predicting household motor vehicle ownership based on utility theory. Rich et al. [7] developed a motor vehicle ownership prediction model based on the utility relationship between workplace, household factors, and vehicle ownership. For electric vehicles, Wang Zhongyang et al. [8] used the elasticity coefficient method and the per capita ownership method to construct a model for predicting the ownership of electric vehicles in Shaanxi Province. Wang Biao et al. [9] predicted the scale of electric vehicle development in the central urban area of Qiqihar by combining various factors influencing the development of electric vehicles. Zhou Hao et al. [10] established a system

dynamics model to determine the scale of electric vehicle development, simulate the trend of electric vehicle development, and analyze the development of electric vehicles under different conditions and scenarios. Tong Fang et al. [11] considered macroeconomic and policy factors, as well as microfactors such as car prices, to establish a multifactor-controlled model for predicting the ownership of new energy vehicles. Park et al. [12] constructed a system dynamics model for the long-term forecasting of vehicle ownership, combining the analysis of macroeconomic factors, policies, technological development, electricity, and other factors affecting energy conversion efficiency. Li Qiang et al. [13] comprehensively analyzed the indirect influencing factors of electric vehicle ownership, such as technology, policies, environment, and social and economic development levels, using the LSTM-SD combined model to make medium- to long-term forecasts of electric vehicle ownership. In recent years, some diffusion models and gray prediction models have also been widely applied in the research of electric vehicle ownership prediction. Chu Yanfeng et al. [14] constructed Bass and GM (1,1) prediction models based on historical data and further used genetic algorithms to predict the ownership of electric vehicles in China from 2020 to 2030. Li Nan et al. [15] used BP neural networks and gray prediction in combination with historical data to make medium- to long-term forecasts of electric vehicle ownership.

With the explosive growth in the number and types of transport vehicles, the issue of energy consumption has attracted widespread attention. Accurately predicting the energy demand of transport vehicles has become an important topic for energy conservation, emission reduction, and sustainable development. Traditional forecasting methods mainly include time series forecasting, regression analysis, and expert evaluation. However, traditional forecasting methods have not fully taken into account the dynamics and uncertainties of energy use in transport vehicles, leading to inherent limitations in the accuracy of prediction data. Luo Zhuowei et al. [16] developed a model to classify the charging time distribution of vehicles using different charging methods and predict the charging load of vehicles. Yang Bing et al. [17] modeled the charging demand of electric vehicles and studied influencing factors, using the Monte Carlo method to model and predict the charging demand of commuter vehicles. Lopez et al. [18] considered temperatures in different regions when building forecasting models to improve prediction accuracy in extreme weather conditions and used a hybrid prediction model combining neural networks for real-time forecasting. Gong L et al. [19] estimated the charging demand and range of electric vehicles using a Monte Carlo model and validated it using the load model of a charging station in Shanghai. Scholars' research has greatly enriched the field of new energy electric vehicles, forming a complex and nonlinear system of interrelated and mutually influential research areas. Pourmatin M et al. [20] used a system dynamics model to predict the future composition of Iran's vehicle fleet by simulating the penetration rates of five different vehicle types. This emphasizes that an increase in fuel prices does not constitute a sustainable long-term intervention for reducing fuel consumption. The model predicts fuel consumption and CO_2 emissions up to the year 2040. However, current research still faces many challenges: Firstly, the short development time of new energy vehicles leads to a lack of sufficient historical data. The existing gray prediction and neural network models only consider historical data, resulting in significant prediction errors. Secondly, scholars face difficulty in quantifying national policies supporting new energy vehicles, and there is limited consideration of policy lag in the literature. Thirdly, there is insufficient systematic consideration of the comprehensive impact of various factors such as consumer preferences, technological development, policy evolution, and the environment on the ownership of electric vehicles. System dynamics perform well in addressing these issues by capturing the dynamic changes in complex systems through feedback loops. They effectively handle the lack of historical data and can simulate the interaction of different factors under various scenarios, providing decision-makers with deep insights into future trends. In predicting the complex, multifactorial nature of electric vehicle ownership, they allow adjustments based on specific policy changes and market dynamics, offering a more comprehensive solution than traditional methods.

Given the complexity and nonlinearity of the research field, this study quantifies impact indicators of vehicle ownership and systematically considers the comprehensive effects of multiple influencing factors on long-term forecasting results. It establishes a motor vehicle ownership prediction model based on system dynamics that takes into account the penetration of electric vehicles, simulates different policy intensities, and obtains predicted values for vehicle ownership and energy demand. This model can guide the government in formulating transportation and energy policies and provide a reference basis for future energy deployment in the country.

2. Factors Influencing EV Ownership

As EVs are entering a period of rapid development, they are forming a complex socio-economic system that encompasses numerous subsystems. EV ownership quantity is influenced by both the increase in new purchases and the decrease in scrappage. The new purchase volume is determined by both the purchasing volume of the automotive market and the relative attractiveness of EVs. The purchasing volume of the automotive market includes the replacement demand arising from vehicle scrappage as well as the additional demand generated by socio-economic development. The relative attractiveness of EVs, defined as the proportion of EV purchases to total automotive purchases, is influenced by various complex factors. Building on existing research, this study combines model selection with factors such as demand for new energy vehicles, policy subsidies, fuel prices, charging infrastructure development, consumer purchase intentions, technological advancements, and charging duration for a comprehensive analysis (Figure 1).

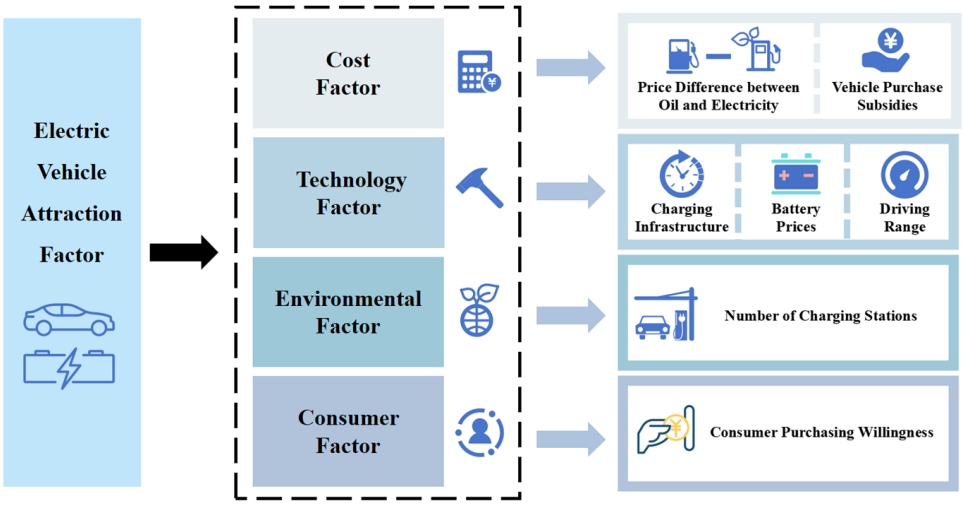


Figure 1. Electric vehicle attraction factor reason tree.

As shown in the above figure, factors influencing the proportion of EV purchases include cost factors (price difference between gasoline and electricity, purchase subsidies), technological factors (charging infrastructure, range capability, and battery prices), consumer factors (consumer purchase intentions), and environmental factors (number of charging stations). These factors interact to determine consumer willingness to choose EVs, thereby affecting the market share of EVs in the overall automotive market. Table 1 provides a description of the data sources used for the aforementioned influencing factors.

Table 1. Summary table of data source descriptions.

Influencing Factors		Data Sources
Cost Factors	Price Difference between Oil and Electricity	East Money, State Grid
	Vehicle Purchase Subsidies	Ministry of Finance
Technology Factors	Charging Infrastructure	IEA
	Battery Prices	BNEF
	Driving Range	IEA
Environmental Factors	Number of Charging Stations	IEA
Consumer Factors	Consumer Purchasing Willingness	Research Report

2.1. Cost Factors

Car purchasing decisions typically involve considering the retail price, available subsidies, and lifetime operating costs, collectively forming the total cost of ownership (TCO). EV purchase subsidies help reduce the total cost of ownership of electric vehicles relative to internal combustion engine vehicles in various ways. With advancements in battery technology and economies of scale, the price of EVs is gradually approaching, and in some cases, even falling below that of traditional gasoline cars. Models like the Tesla Model 3 and BMW 3 Series, as well as the Nissan Leaf and Ford Focus, have very similar price points, with some EVs becoming even more competitive. This trend is expected to accelerate, further increasing the market penetration of EVs and providing stronger support for the green transition.

2.1.1. Purchase Subsidies

The impact of purchase subsidy factors is reflected as follows: ① New energy vehicle purchase subsidy policy: China began implementing the purchase subsidy policy in 2016, adopting a gradually decreasing financial support measure, and planned to end national subsidies for new energy vehicles by the end of 2022. ② New energy vehicle purchase tax subsidy policy: by the end of 2022, the accumulated amount of purchase tax exemptions exceeded CNY 200 billion, and the exemption period for new energy vehicle purchase tax was to be extended as an important measure of national financial incentives by the end of 2023.

2.1.2. Price Difference between Gasoline and Electricity

The impact of the gasoline–electricity price difference factor is reflected as follows: ① Government support policies: from 2014 to 2020, the country issued a series of preferential pricing policies for charging infrastructure, adopting an industrial electricity pricing system for centralized charging and swapping station facilities and completely canceling basic electricity fees. Before 2025, a two-tier pricing mechanism will be implemented, exempting electricity charges for basic electricity demand (capacity). ② Gasoline prices: from 2015 to 2023, global gasoline prices experienced significant fluctuations. Various factors such as fluctuations in international crude oil prices, the impact of geopolitical events, and changes in market supply and demand relationships will collectively affect gasoline prices, which have generally shown an upward trend. ③ Public charging station charging prices: due to the varying prices of public charging stations based on different time periods, regions, and operators, the average public charging fee is set as follows for simplicity: from 2015 to 2019, the charging fee was CNY 0.5 per kilowatt-hour (including operator service fees); from 2020 to 2023, the charging fee was 0.8 CNY per kilowatt-hour (including operator service fees).

2.2. Technological Factors

2.2.1. Driving Range

The driving range of EVs is an important economic performance indicator for electric cars. According to the International Energy Agency's Global Electric Vehicle Outlook report for 2024, data show that from 2015 to 2023, the weighted average range of battery electric vehicles increased by nearly 75% due to the increase in battery size and improvements in battery technology and vehicle design. Currently, the range of medium-sized cars and SUVs has seen significant improvements, with a range of approximately 380 km. This improvement in the range of medium-sized cars and SUVs could stimulate consumption among potential users who are interested in purchasing EVs for long-distance travel.

2.2.2. Battery Prices

In the architecture of new energy vehicles, the battery serves as the core power unit, accounting for approximately 30% to 40% of the total vehicle cost. For users of electric vehicles, it is necessary to consider the battery's lifespan, replacement cost, and potential impacts comprehensively. According to a report on battery costs by BNEF, the price of lithium-ion battery packs increased by 7% in 2022 compared to 2021 due to fluctuations in the market for battery metals. In 2023, the trend reversed, with the price of lithium-ion batteries dropping to an average capacity-weighted level of USD 139 per kilowatt-hour.

2.2.3. Charging Infrastructure

In China, there are mainly two types of charging equipment for electric vehicles, namely alternating-current chargers (slow chargers) and direct-current chargers (fast chargers). According to the latest statistical report from the Charging Alliance, by the end of 2023, all member companies of the alliance had reported a total of 2.726 million publicly available charging piles, including 1.203 million AC charging facilities. By predicting the proportion of fast chargers at charging points to calculate the speed of charging, with an average duration of 60 min for fast charging and 480 min for slow charging, the charging factor is calculated to assess its impact on the attractiveness of purchasing EVs.

2.3. Environmental Factors

China actively promotes the construction of charging stations and has currently established the world's largest coverage of charging service networks. According to IEA data, in 2023, the ratio of low-emission vehicles (LEVs) to electric vehicle supply equipment (EVSE) in China is 8, with an average public charging power of 3.4 kW per electric LDV. A high EVSE ratio can inconvenience consumers, while excessive infrastructure can lead to inefficiencies. Finding the right balance is crucial to ensuring optimal utilization and the satisfaction of EV users.

2.4. Consumer Factors

In the early stages of EV development, although the government provided substantial financial subsidies to encourage private purchases, the technology and market were still being cultivated, public infrastructure was incomplete, and vehicle sales growth was slow, leading to low consumer purchasing willingness. In the mid-term of EV development, following the impact of the COVID-19 pandemic, the importance of cars as protected private spaces was strengthened, and consumers were more inclined to own their own vehicles. Since 2020, with the reduction in subsidies, the impact of the COVID-19 pandemic, and the downturn of the macroeconomy, these negative effects have gradually been being absorbed. At the same time, issues such as short range and charging difficulties are slowly being alleviated, and the market acceptance of new energy vehicles is also increasing.

3. Predictive Models for Vehicle Ownership Quantity and Energy Demand

System dynamics, introduced by Forrester and others in 1956, constitute a modeling approach that analyzes the interactions and feedback mechanisms within a system. This

approach considers time delays and dynamic behaviors to describe the dynamic characteristics of complex systems and evaluate the impact of various policies [21]. Using system dynamics to explore core issues involves constructing a model framework closely approximating real-world scenarios and using simulation software Vensim PLE x64 to model and analyze the system's functional properties and dynamic evolution. The process of building a model tailored to real-world problems can be summarized in the following steps (Figure 2).

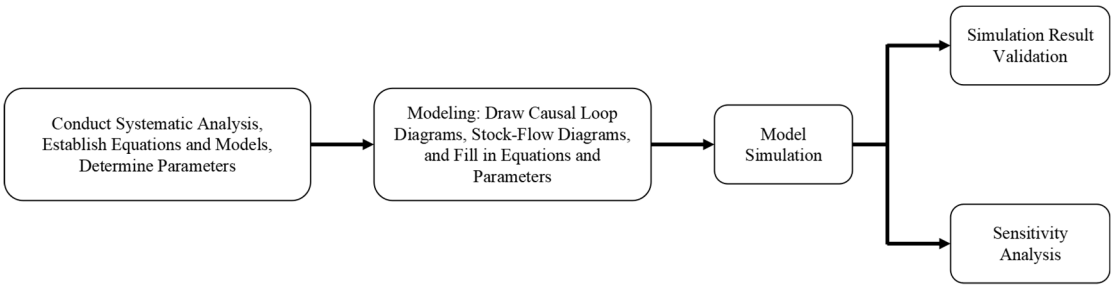


Figure 2. Theoretical model of system dynamics.

3.1. Defining the System

By referencing statistical yearbooks and data from the Chinese Traffic Management Bureau, one study focuses on the vehicle fleet structure consisting of gasoline and electric vehicles, given the limited presence of hydrogen-powered cars [22]. The study primarily concentrates on light vehicles to align with the data used, considering the significant differences in energy consumption, range, and policy support between light and heavy vehicles.

3.2. Assumptions

The basic assumptions include ① ensuring vehicle ownership quantity equals vehicle usage quantity; ② excluding irrelevant factors to maintain data reliability and model simplicity; ③ assuming overall stable economic development within the simulation period; ④ assuming a positive correlation between research investment and technological advancement; ⑤ modeling the inherent changes in the new energy vehicle system without delving deeply into specific policy effects.

3.3. Establishing Causal Relationships

Vehicle demand stems mainly from economic stimuli for first-time buyers and replacement needs for existing car owners. These demands, bolstered by various incentive policies, translate into purchasing motivations, leading to an increasing proportion of annual new energy vehicle purchases. Factors such as vehicle charging costs, charging time, purchase subsidies, and range significantly influence consumer decisions, forming the basis for constructing predictive models for vehicle ownership quantity and energy demand (Figure 3).

The causal diagram encompasses numerous feedback loops, totaling 28 primary causal feedback cycles starting from energy consumption calculations. These cycles consist of 14 positive feedback loops and 14 negative feedback loops (Figure 4). In the first feedback loop, the increase in energy consumption prompts the government to strengthen its support for new energy vehicles. This leads to reinforced investments in purchase subsidies, the price difference between oil and electricity, driving range, battery prices, charging infrastructure, and charging stations. Consequently, factors such as technology, the environment, costs, and consumer appeal are enhanced, elevating the attractiveness of EVs. This, in turn, boosts EV purchases, increases the EV ownership ratio, and reduces energy consumption, forming a negative feedback loop. Simultaneously, the second feedback loop further diminishes the purchase volume of CVs, increases the EV ownership ratio, and reduces energy consumption, creating a negative feedback loop. Building upon the second

feedback loop, the third and fourth feedback loops introduce metrics such as CV and EV scrappage rates, replacement purchases, overall vehicle acquisitions, CV purchase quantity, EV purchase quantity, CV ownership quantity, and EV ownership quantity, establishing positive causal feedback loops.

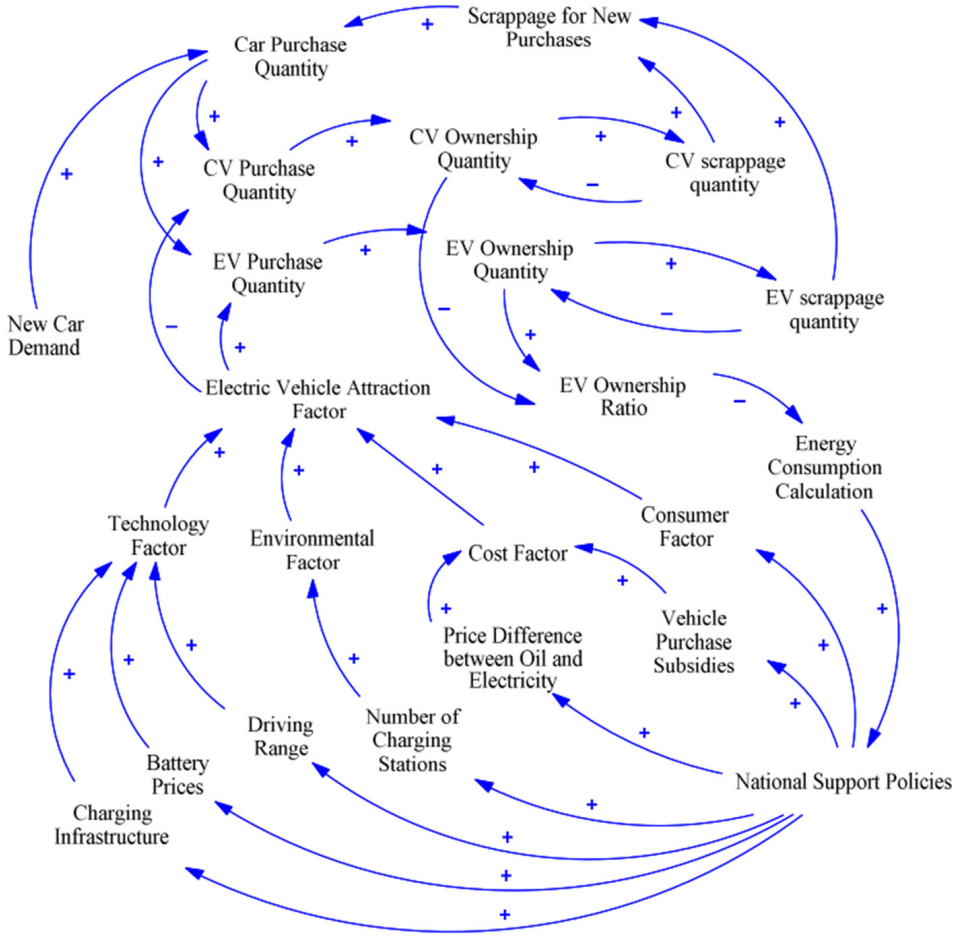
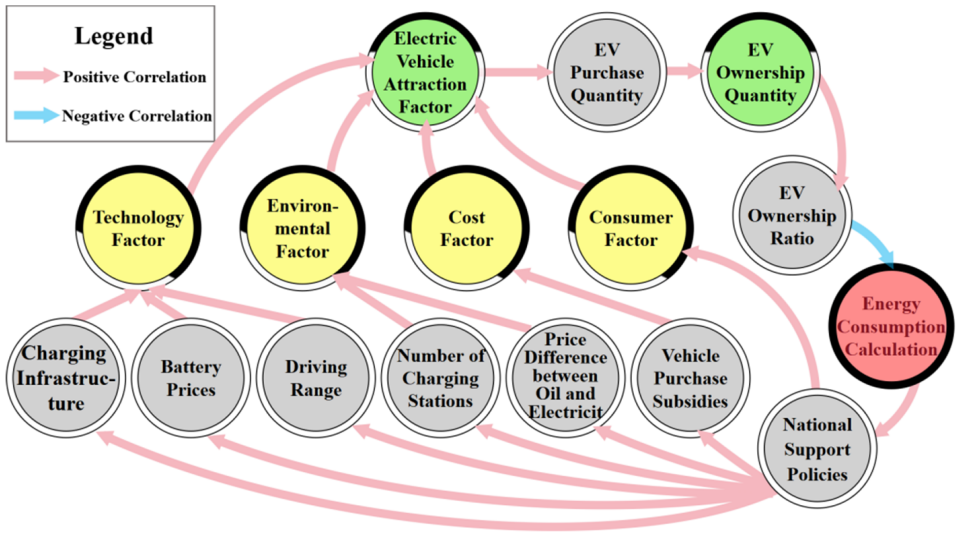
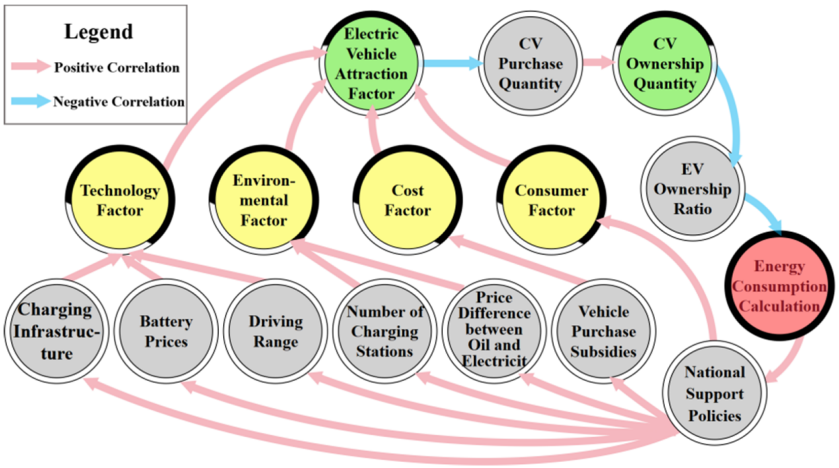


Figure 3. System dynamics causality diagram.

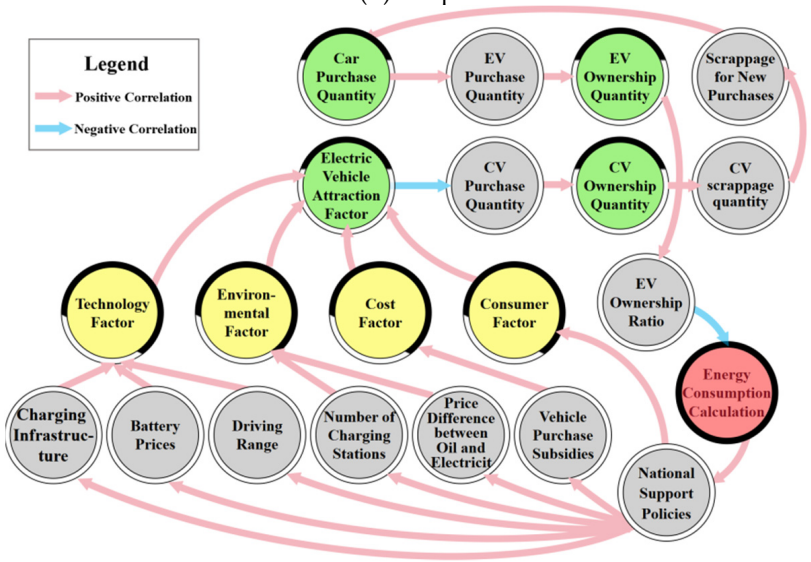


(**a**) Loop 1

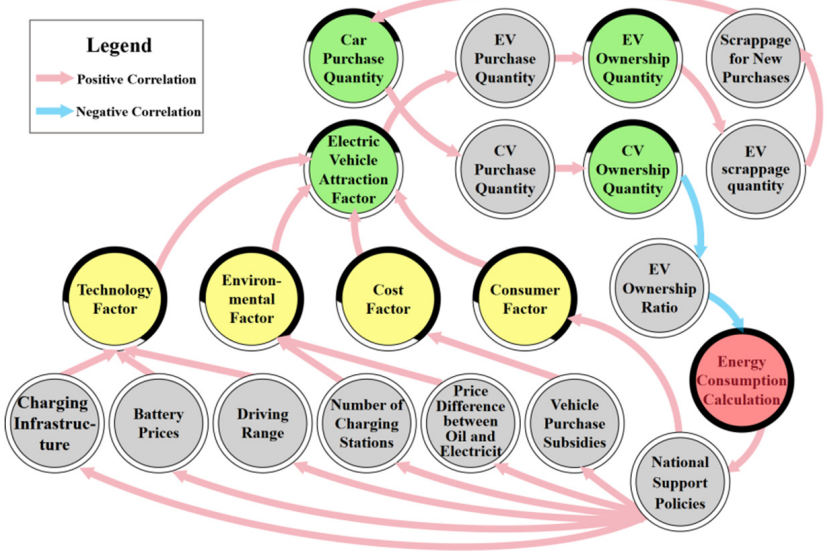
Figure 4. *Cont.*



(**b**) Loop 2



(**c**) Loop 3



(**d**) Loop 4

Figure 4. Causal feedback loops.

3.4. Flow Charts and Key Model Equations

This study establishes a predictive model for vehicle ownership quantity and energy demand based on the interrelationships among various internal elements using system dynamics, as shown in Figure 5. Factors like technology, the environment, cost, consumer factors, range, battery prices, charging infrastructure, subsidies, and the price difference between oil and electricity are normalized to real numbers ranging from 0 to 1. These variables exhibit nonlinear changes, with consumer factors, range, battery prices, charging infrastructure, subsidies, and the price difference between oil and electricity being handled through tabular functions, as shown in Table 2.

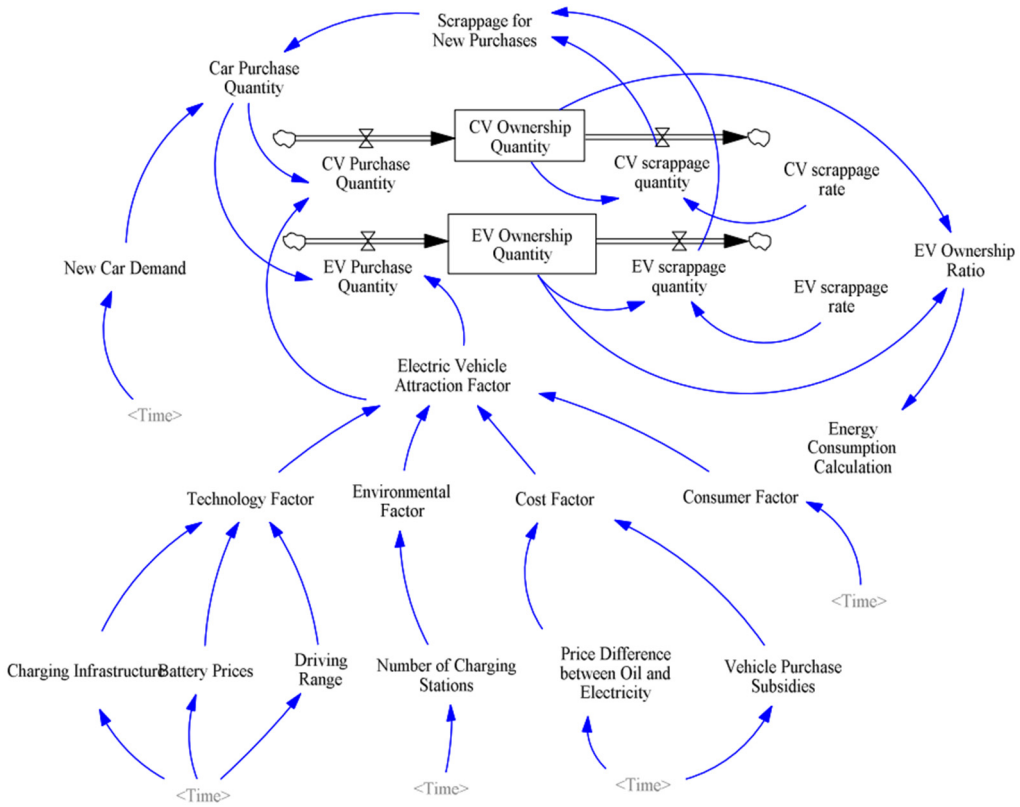


Figure 5. System dynamics flow level and flow rate diagram.

Table 2. Main dynamic equations of system dynamics model.

Variable Types	Main Variables and Equations
Level Variables	CV Ownership Quantity = INTEG (CV Purchase Quantity − CV Scrappage Quantity, Initial Value) EV Ownership Quantity = INTEG (EV Purchase Quantity − EV Scrappage Quantity, Initial Value)
Rate Variables	CV Purchase Quantity = (1 − Electric Vehicle Attraction Factor) × Car Purchase Quantity EV Purchase Quantity = Electric Vehicle Attraction Factor × Car Purchase Quantity CV Scrappage Quantity = CV Scrappage Rate × CV Purchase Quantity EV Scrappage Quantity = EV Scrappage Rate × EV Purchase Quantity
Auxiliary Variables	Car Purchase Quantity = New Car Demand + Scrappage for New Purchases Scrappage for New Purchases = EV Scrappage Quantity + CV Scrappage Quantity Electric Vehicle Attraction Factor = (γ_1 Technology Factor + γ_2 Environmental Factor + γ_3 Cost Factor) × Consumer Factor Technology Factor Driving Range + α_2 Battery Prices + α_3 Charging Infrastructure Cost Factor = β_1 Vehicle Purchase Subsidies + β_2 Price Difference between Oil and Electricity

3.5. Energy Consumption Calculation Formula

Predicting future energy demand involves calculating the energy consumption proportions of electric and gasoline vehicles in traffic flow. This calculation is crucial for multilevel planning and decision-making. The energy consumption calculations for light electric and gasoline vehicles are based on the formula provided in reference [23], where various parameters such as average travel speed and flow rate are considered, with specific values assigned for simulation under urban driving conditions. The relevant parameters for light electric and gasoline vehicles are detailed in the accompanying table.

$$e_{\overline{v}} = F_{\overline{v}} q_{f,\overline{v}} \tag{1}$$

$$F_{\overline{v}} = a_1 + b_1 \overline{v} + c_1 r_1^{\overline{v}} \tag{2}$$

where $e_{\overline{v}}$ is the energy of the average travel speed, $\overline{v}\left(\mathrm{km{\cdot}h^{-1}}\right)$; $q_{f,\overline{v}}$ is the flow rate of $\overline{v}\left(\mathrm{km{\cdot}h^{-1}}\right)$ and the three-parameter basic graph model $\left(\mathrm{veh{\cdot}h^{-1}}\right)$; and the flow rate takes a fixed value of 1000 $\left(\mathrm{veh{\cdot}h^{-1}}\right)$. The Urban Dynamometer Driving Schedule (UDDS) conditions are used to simulate the state of urban road driving, and the average speed is $31.5/\left(\mathrm{km{\cdot}h^{-1}}\right)$. The relevant parameters of light electric vehicles and fuel vehicles are shown in the Table 3.

Table 3. CV and EV energy consumption measurement formula parameters.

Parameter	CV	EV
a_1	488.236	−95.455
b_1	−1.034	7.877
c_1	2971.091	805.761
r_1	0.914	0.964

4. Case Study and Results

4.1. Basic Data for the Case Study

This study utilizes national data from China, obtaining foundational data from statistical yearbooks and employing Vensim PLE x64 to simulate and forecast the stock trends of CVs and EVs from 2024 to 2035. Specific parameter data values and sources are presented in the Table 4.

Table 4. Initial values and sources of parameter values.

Name	Value	Source
CV Scrappage Rate	0.15%	Reference [13]
EV Scrappage Rate	0.1%	Reference [13]
Initial Value of CV Ownership Quantity	27,607.98 Million Vehicles	Ministry of Public Security Traffic Management Bureau
Initial Value of EV Ownership Quantity	492.02 Million Vehicles	Ministry of Public Security Traffic Management Bureau
Driving Range	Table Function	IEA
Battery Prices	Table Function	BNEF
Charging Infrastructure	Table Function	IEA
Technology Factor Coefficient, $\alpha_1, \alpha_2, \alpha_3$	0.4, 0.3, 0.4	Reference [24]
Number of Charging Stations	Table Function	IEA
Vehicle Purchase Subsidies	Table Function	Ministry of Finance
Price Difference between Oil and Electricity	Table Function	East Money, State Grid
Cost Factor Coefficient, β_1, β_2	0.3, 0.7	Reference [13]
Consumer Factor	Table Function	Research Report
Electric Vehicle Attraction Factor, $\gamma_1, \gamma_2, \gamma_3$	0.35, 0.3, 0.35	Reference [24]

4.2. Model Validation

The validation of the model in this study is divided into two parts: model operational testing and historical data validation. The simulation step sizes were set at 0.25, 0.5, and 1 to compare the simulated EV ownership quantity results. The results indicate minimal variation in the simulated curve and data trends of EV ownership quantity, suggesting that the model does not produce erratic results due to performance issues, as shown in Figure 6.

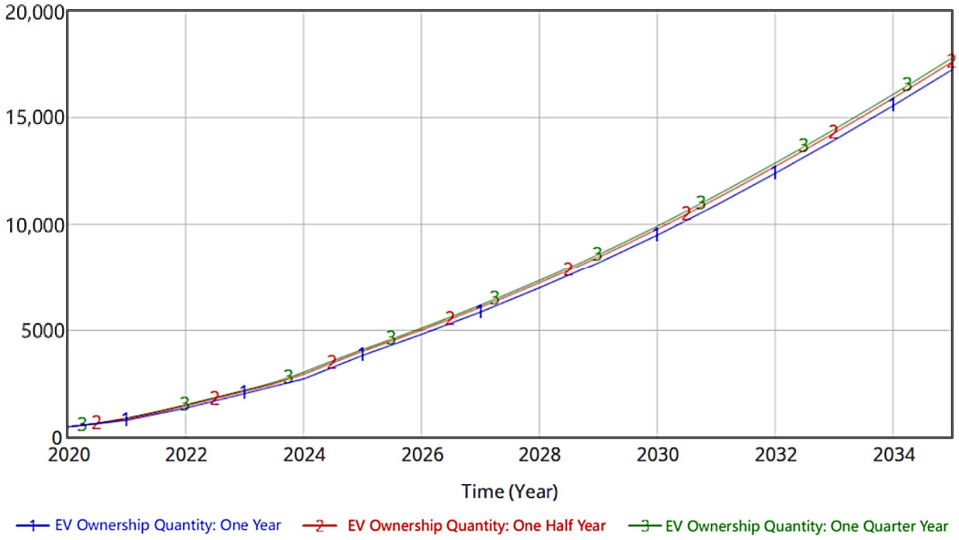


Figure 6. Comparative chart of EV ownership quantity at different time steps (unit: 10,000 vehicles).

Historical validation involves comparing the model-simulated output with actual historical data. By assessing the deviation between the simulated results and empirically measured values of key variables, the degree of error is quantified in terms of the relative error using the following formula:

$$\text{Relative Error} = (\text{Simulated Value} - \text{Actual Value}) / \text{Actual Value} \quad (3)$$

This study employs historical statistical data on CV and EV ownership quantity from 2021 to 2023 as a baseline for comparison with the model simulation results. The relative errors between the simulated and historical data for EV and CV ownership quantity are within 5% (Tables 5 and 6), indicating a good historical fit for the model. By utilizing the model for simulation, the simulated data effectively represent the development trends of new energy electric vehicles, enabling the prediction of energy demand in transportation flows.

Table 5. Comparison of real and projected values of EV ownership quantity.

Year	Historical Data /Million Vehicles	Simulation Data /Million Vehicles	Relative Error/%
2021	784	795.66	1.49%
2022	1310	1366.53	4.32%
2023	2041	2046.45	0.27%

Table 6. Comparison of real and projected values of CV ownership quantity.

Year	Historical Data /Million Vehicles	Simulation Data /Million Vehicles	Relative Error/%
2021	30,200	29,487.2	−2.36%
2022	31,900	31,104.8	−2.49%
2023	33,600	32,218.2	−4.11%

4.3. Analysis of Simulation Results

4.3.1. Simulation Analysis under Baseline Scenario

The model simulated the period from 2020 to 2035 with a yearly time step, predicting simulated curves and data for the ownership quantity of CVs and EVs (Figure 7). The simulated curve for EV ownership quantity shows a steady annual growth trend. Initially, due to subsidy reductions, the growth rate of the EV ownership quantity is relatively low. However, as key technical parameters such as range, charging time, and battery prices improve, electric vehicles mature in various aspects. Consumer acceptance of electric vehicles increases, leading to a rapid growth trend in EV ownership quantity, aligning with national incentive policies. Economic expansion results in a comprehensive growth in vehicle stock. In the early simulation period, the growth rate of the CV ownership quantity exceeds that of the EV ownership quantity. Over time, the CV ownership quantity curve significantly slows down and stabilizes.

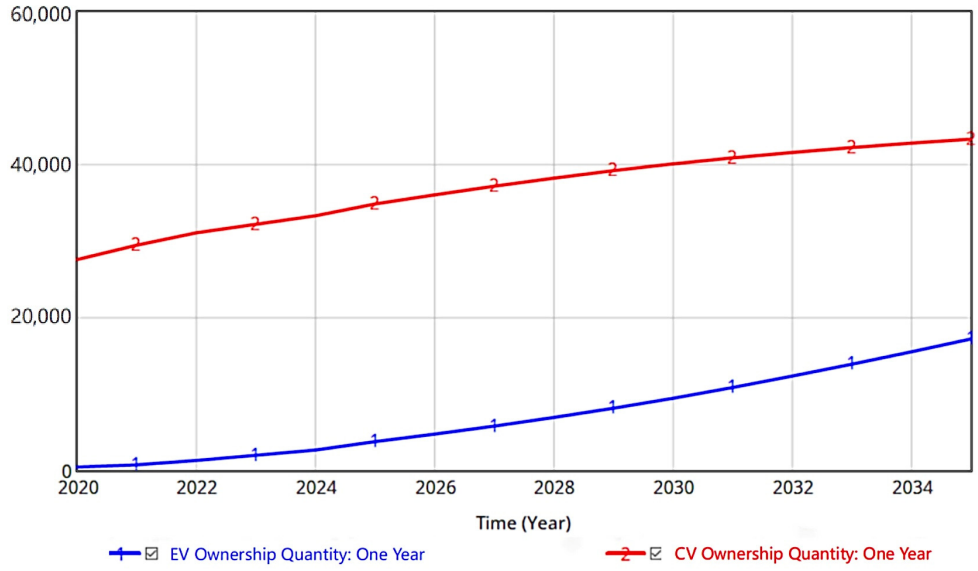


Figure 7. EV and CV ownership quantity simulation curves (unit: 10,000 vehicles).

The simulation also yielded curves for the proportion of EV ownership and energy consumption per thousand vehicles (Figure 8). The proportion of EV ownership increases annually, with the simulated EV proportion reaching 5.9725% in 2023, close to the actual value of 6%, validating the model's accuracy. As the proportion of EV ownership increases, it is projected to reach 26.6543% by 2035. The energy consumption per thousand vehicles under the UDDS conditions decreases annually, demonstrating the expected effect.

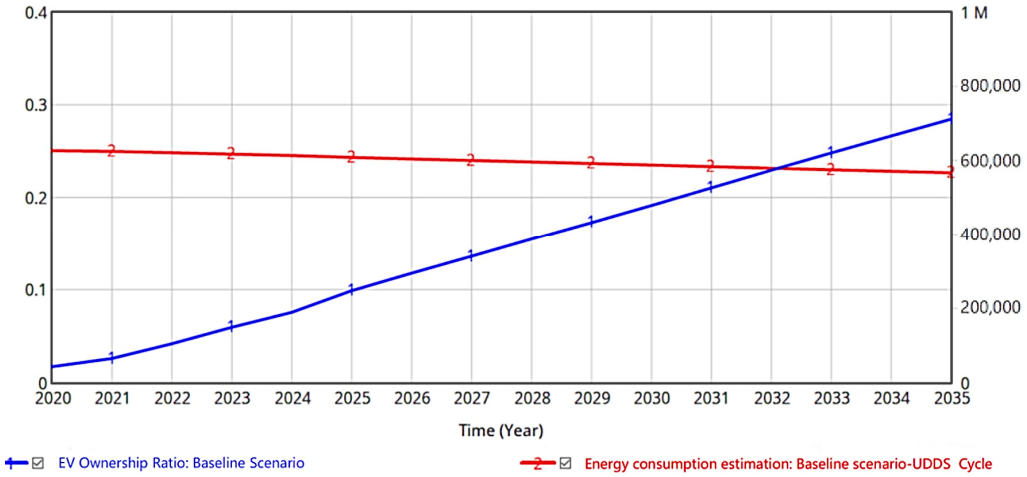


Figure 8. Simulation curve of EV ownership ratio and energy consumption (unit: J/km).

4.3.2. Simulation Analysis under Different Policies

The development path and trends of the electric vehicle industry vary in response to different development stages, dynamic environmental factors, political situations, and other relevant elements. To analyze energy demand in transportation flows under different policy states, scenarios one and two were simulated based on the study of national policy impacts. ① Baseline Scenario: under existing policy plans, technical and environmental factors continue to evolve according to current trends, with the introduction of a new energy vehicle purchase tax starting in 2028. ② Scenario one: building upon the baseline scenario, technical and environmental factors are increased by 20%. New energy vehicle purchase tax exemptions are granted in 2026–2027, halved in 2028–2029, and fully imposed from 2030 onwards. ③ Scenario two: building upon the baseline scenario, technical and environmental factors are increased by 40%. New energy vehicle purchase tax exemptions are granted in 2026–2029 and halved from 2030 to 2035.

Different policy intensities are set to promote the development of new energy vehicles. The simulation predicts the national ownership quantity of CVs and EVs, the EV ownership ratio, and the energy consumption per thousand vehicles under three different development levels (Figures 9 and 10).

Investments in policy and the economy impact the growth of the EV and CV ownership quantity and energy demand in transportation flows. Under the baseline scenario, the national ownership quantity of EVs and CVs is projected to reach 172.43 million and 433.36 million vehicles, with EVs comprising 28.4644% of the total stock with an energy consumption of 566,781 J·km^{-1} per thousand vehicles by 2035. In scenario one, strengthened new energy policies drive the growth of the EV ownership quantity, with the national EV and CV ownership quantity reaching 186.01 million and 419.59 million vehicles by 2035. EVs comprise 30.715% of the total stock, with an energy consumption of 561,740 J·km^{-1} per thousand vehicles. In scenario two, with further support for new energy vehicle policies and enhanced technological maturity, the national EV and CV ownership quantities are projected to reach 201.276 million and 404.106 million vehicles by 2035. EVs comprise 33.2478% of the total stock, with an energy consumption of 556,067 J·km^{-1} per thousand vehicles, surpassing 200 million new energy vehicles. Under different policy incentives, the energy demand for traffic flow varies significantly. Strengthening supportive policies for new energy incentives will promote the construction and development of the new energy industry, attracting more investors and consumers into the electric vehicle market, thereby advancing the electrification of road transport in the transportation sector. To facilitate the green transition of transportation nationwide, it is essential to enhance policy coordination and increase economic investment. The active promotion of policies has had a notable impact on the electrification of vehicles, and investments in vehicle performance technologies will also yield returns. China still has tremendous potential for development

in its green transition, which will help accelerate the peak of carbon emissions and achieve the goal of carbon neutrality.

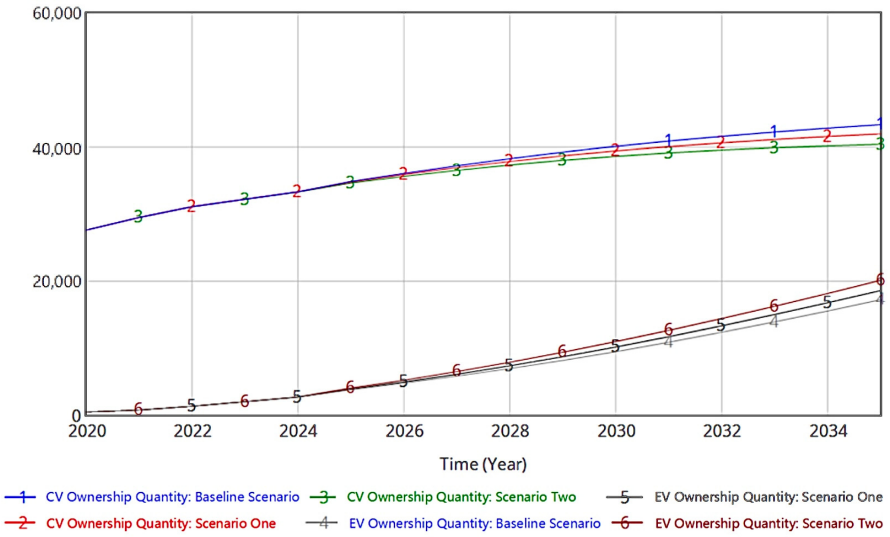


Figure 9. Simulation of EV and CV ownership quantity under different policy intensities (unit: 10,000 vehicles).



(**a**) (**b**)

Figure 10. (**a**) Simulation of EV ownership ratio under different policy intensities; (**b**) simulation of energy consumption under different policy intensities (unit: J/km).

5. Conclusions

This study, starting from changes in the composition of traffic flow fleets, considers the different influencing factors on EV and CV ownership quantity and energy consumption calculations. By employing system dynamics methods to establish models for predicting vehicle stock and energy demand, this research compares and analyzes the trends in EV and CV ownership quantity and energy consumption per thousand vehicles under the baseline scenario, scenario one, and scenario two. The following conclusions were drawn:

New energy vehicles are experiencing rapid development. While subsidies for new energy vehicles are declining, government policies remain a key driver of their growth. The continued development of EV technology and charging infrastructure will further drive the growth of new energy vehicles in China.

Planning for energy demand should be carried out in advance based on the unique characteristics of different regions. Strengthening infrastructure development and providing appropriate charging facilities, alongside promoting fast and supercharging stations and implementing reasonable charging pricing policies, will enhance charging services for EV users.

Increasing consumer acceptance of new energy electric vehicles and vigorously developing the domestic market for new energy electric vehicles are crucial. Governments, businesses, and various social groups should leverage online platforms to promote the energy-saving and environmentally friendly characteristics of new energy vehicles. Efforts should also focus on promoting the demonstration and popularization of new energy electric vehicles to enhance consumer awareness and acceptance.

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