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2023 APMCM summary sheet

China New Energy Electric Vehicle Industry Trend Forecast and Strategy Research

Summary

This comprehensive study employs five models to analyze the new energy electric vehicle industry. It identifies critical development factors, predicts China's sales over the next decade, evaluates the global impact on the traditional automobile industry, and examines the effects of foreign policies. Additionally, it explores the ecological impact of urban electric vehicles. These models provide a multi-faceted view, offering valuable insights for policy making and industry growth.

Question 1: This question uses a multi-dimensional model to identify key factors influencing new energy vehicle development, focusing on policy, economy, market, and vehicle specifics. By analyzing correlation coefficients and indicator variability, it highlights the most impactful factors, such as GDP per capita, subsidies, pricing, urbanization, and charging infrastructure, all showing strong correlations with sales. This aids in policy and strategic industry planning.

Question 2: Utilizing ARIMA and gray forecasting models, the study accurately predicts China's new energy vehicle sales for the next decade. ARIMA processes historical data, and gray forecasting addresses incomplete information, enhancing market prediction accuracy. These methods are crucial for understanding industry trends and guiding strategic and policy development.

Question 3: Employing a dynamic model combining scenario reconstruction and evolutionary games, this study explores the interaction between new and traditional energy vehicle industries. It considers factors like technology and policy changes, predicting that new energy vehicles, bolstered by policy and low usage costs, will increasingly impact the global auto industry. A time series model quantifies this impact, offering precise future industry trend predictions.

Question 4: Multiple linear regression and exponential regression models were used to quantify the impact of foreign boycott policies on China's new energy vehicle industry. We analyzed factors such as tariffs and investment restrictions, and used statistical methods to assess the potential impact of these policies on the market, providing a quantitative basis for the response strategies of China's new energy vehicle industry. Conclusion: Model analysis shows that the exchange rate is the main factor inhibiting the development of new energy vehicles in China, followed by tariff changes in the United States and Germany, with Germany in particular having a more significant impact. Although foreign investment currently has a positive impact on the industry, the effect is relatively weak and likely to be lagged, and may become a dampening factor in the future.

Question 5: This question models the ecological impact of new urban energy electric vehicles, incorporating penalty factors adaptable to varied urban traits and considering energy and carbon emissions data. Findings reveal that electric sedans significantly reduce CO2, while medium to large electric buses have a lesser impact. Overall, vehicle electrification positively affects the environment, effectively lowering carbon emissions and aiding in urban planning and environmental policy-making.

Question 6: The purpose of this open letter is to highlight the findings of issue 5, namely the positive ecological impact of electrification of new energy vehicles. We will communicate the benefits and industry contributions of new energy electric vehicles to promote their importance.

Keywords: Sales Volume Forecasting; ARIMA Model; Evolutionary Game; Multiple Linear Regression; Penalty Factor

CONTENTS

1. Restatement of the Problem

1.1. Background to the Issue

The rise of new energy vehicles, especially electric vehicles (EVs), signifies a major transformation in the global automotive industry. These vehicles, utilizing innovative fuels like electricity and advanced power control technologies, are noted for their low environmental impact and high energy efficiency. China has been instrumental in advancing this industry through policies since 2011, bolstering domestic growth and international competitiveness. This development marks a significant step in China's industrial modernization and contributes substantially to environmental protection and sustainable development goals. The adoption of EVs reduces greenhouse gas emissions, enhances energy efficiency, and improves urban air quality, transcending mere technological advancement to become a crucial element in global ecological and energy structure optimization. New energy vehicles represent the future of the automotive sector and China's leadership in new energy technologies and environmental conservation. As the industry evolves with technological progress and market maturation, these vehicles are poised to play an increasingly vital role in global energy and environmental governance. This paper employs various mathematical modeling techniques to provide an accurate forecast of new energy vehicle market sales, reflecting the global trend towards new energy vehicle development.

1.2. Restatement

Question 1: Investigate the key factors influencing China's new energy electric vehicle development and create a mathematical model to elucidate their impact on the industry's growth.

Question 2: Gather data on China's new energy electric vehicle industry and build a mathematical model to predict its development trend over the next decade.

Question 3: Collect data and construct a mathematical model to analyze the impact of new energy electric vehicles on the global conventional energy automotive industry.

Question 4: Construct a mathematical model to analyze the impact of international obstruction policies on China's new energy electric vehicle development.

Question 5: Analyze the ecological impact of urban electric vehicle electrification, including buses, in a city of 1 million, and provide the model's calculations.

Question 6: Based on the findings of Question 5, Compose an open letter highlighting the global benefits and contributions of the new energy electric vehicle industry.

2. Problem Analysis

2.1. Analysis of Question one

In this study's initial phase, we conducted a comprehensive data quality analysis using Python, focusing on identifying and rectifying outliers and missing values to ensure the model's predictive accuracy and reliability.

This study constructs a model to analyze new energy vehicle development, refining primary indicators into impactful secondary indicators like subsidy intensity, GDP per capita, fuel prices, and maintenance costs. Quantitative techniques filter the most impactful indicators, ensuring model validity and providing industry insights.The specific flow chart is shown in Figure 2-1. below.

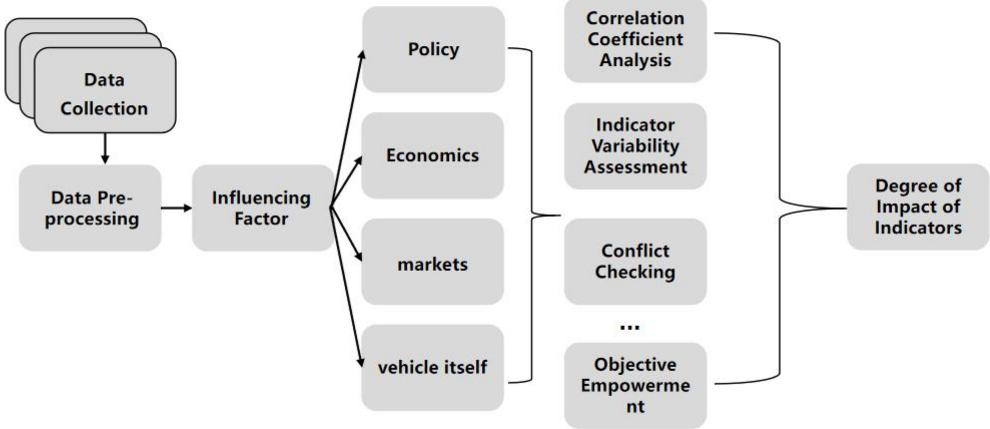

Figure 2-1 Issue 1: Process Visualization

2.2. Analysis of Question Two

This question aims to analyze and predict China's new energy vehicle industry's growth over the next decade, focusing on sales trends as influenced by technological innovation and market dynamics. Utilizing key indicators, we will apply ARIMA and Gray Forecasting Models for an accurate sales forecast. These models are selected for their proficiency in handling time series data, and their accuracy will be rigorously validated. This approach aims to provide detailed insights and precise long-term forecasts for the industry's development.

2.3. Analysis of Question Three

This research assesses the impact of new energy vehicles on the global automobile industry, employing dynamic game theory and scenario reconstruction. Rigorous validation and advanced forecasting provide vital insights into their long-term effects.

2.4. Analysis of Question Four

Our study models the impact of international sanctions, especially from the United States and allies, on China's new energy vehicle industry. Focusing on export restrictions, investment constraints, and tariffs, we employ linear and exponential regression methods, addressing multicollinearity and heteroskedasticity, to quantitatively analyze their effects on key economic factors.

2.5. Analysis of Question Five

The study analyzes the environmental impact of urban electric vehicles, using weighted indicators and city-specific penalty factors to model their energy use and carbon emissions, offering deeper insights into ecological effects.

2.6. Analysis of Question Six

This open letter aims to spotlight our research findings on the ecological benefits of new energy vehicle electrification, underscoring their importance and promoting wider adoption.

3. Model Assumption

Question One Hypothesis

Hypothesis 1: Market equilibrium hypothesis: market conditions (e.g., supply and demand, price) have a significant impact on the demand and supply of new energy electric vehicles.

Question Two Hypothesis

Historical trend continuity assumption: past sales trends can predict future trends.

Question Three Hypothesis

Market competition assumption: new energy vehicles and conventional vehicles compete with each other in the market.

Question Four Hypothesis

External policy intervention hypothesis: foreign policies have a direct impact on China's new energy vehicle market.

Question Five Hypothesis

Environmental improvement hypothesis: the popularization of new energy vehicles will significantly improve the quality of urban environment.

4. Description of Relevant Symbols

notation	clarification
d	difference in order
$\bar{x}$	average value
σ	(statistics) standard deviation
S_j	Standard deviation of the jth indicator
ρ	resolution factor
μ	spontaneity value
γ_i	autocorrelation
φ	Vehicle survival probability
H	Average household size
a	Development of gray numbers in gray prediction models
E_{ev}	Penetration of new energy electric vehicles
$1-E_{ev}$	Prevalence of conventional fuel vehicles

5. Problem 1 Modeling and Solving

Our study meticulously selects data from authoritative sources like the National Bureau of Statistics and automotive associations, ensuring reliability. We've also enhanced data security and quality, detailed in Table 5-1 of our paper.

Table 5-1 Content of Selected Data Sets

particular year	Investment in fixed assets (billions of dollars)	Sales of new energy vehicles (10,000 units)	Kilometers (10,000)	consumer index	urbanization rate	GDP (billions of dollars)
2010	218834	0.5	400	103	48%	397983
2011	238782	0.8	410.6	105	51%	487940
2012	281684	1.3	423.7	102	52%	538580
2013	329318	1.8	435.6	102	53%	592963
2014	373637	7.5	446.3	102	54%	643563
2015	405928	33.1	457.7	101	56%	688858
2016	434364	50.7	469.6	102	57%	746395
2017	461284	77.7	477.3	101	58%	832035
2018	488499	125.6	484.6	102	59%	919281
2019	513608	120.6	550.1	102	60%	990865
2020	527270	136.7	583.2	102	61%	1015986
2021	552884	165.2	603.2	100	62%	1175082
2022	-	201.4	653.2	101	63%	1210207

5.1. Data Preprocessing

Step1 Data Integrity Assessment

Using Python's Pandas library, this study conducted a detailed missing value analysis on its dataset, ensuring data integrity by field. The dataset is confirmed to have no missing values, laying a solid foundation for further analysis, as shown in Figure 5-1.

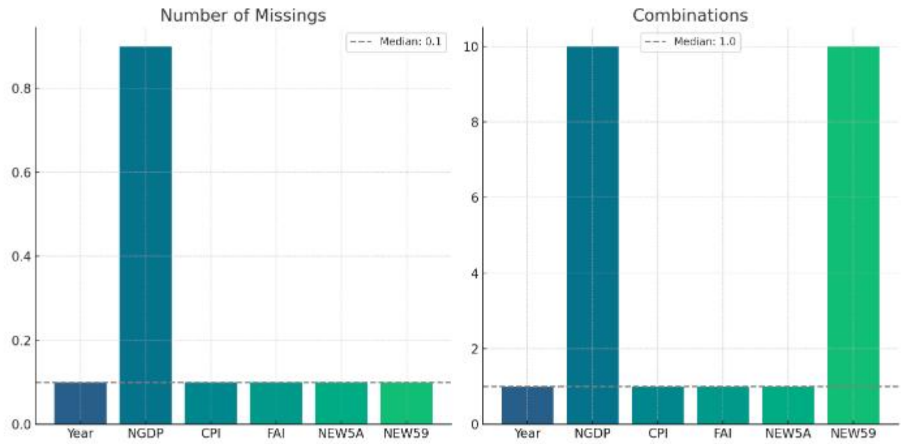

Figure 5-1 Data Integrity Analysis

Step2 Outlier Identification

Abnormal data, hidden yet impactful, were detected and addressed across all fields, significantly improving the model's accuracy. Details are shown in Figure 5-2.

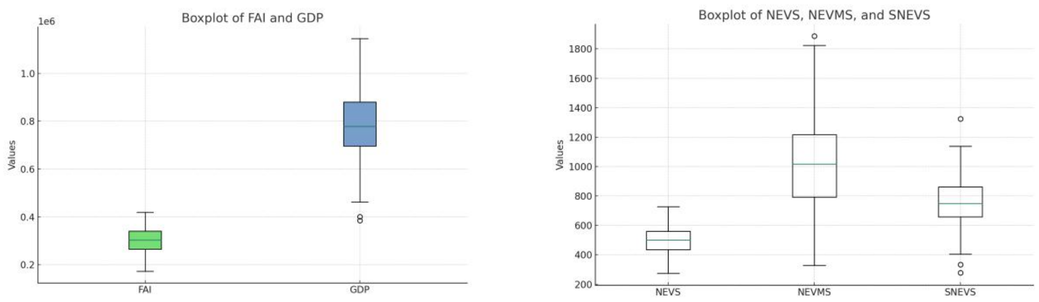

Figure 5-2 Visualization of Anomalous Data Checking

5.2. Modeling

Step1 Establishment of the Indicator System

We meticulously identified and treated anomalous data, which are valid but significantly diverge from the norm, through detailed statistical analysis. The process and results, ensuring data quality and analysis accuracy, are depicted in Figure 5-2.

Table 5-2 Indicator Framework for Constructing Impact Factors to be Screened

Level 1 Indicators	Secondary Indicators
Deal	Vehicle Restriction Management Government Subsidies for Electric Vehicles Carbon Emissions Trading Market Price Vehicle Purchase Tax Reduction Percentage
Economics	Gross Domestic Product (GDP) Per Capita Level of Disposable Income Per Capita Consumer Spending Index (CPI) Urbanization Rate Total Road Network Mileage
Market	Oil Fuel Costs Scale of Electric Vehicle Charging Stations Private Vehicle Ownership Total Industry Investment
Vehicle Itself	Salvage Value (of a car) Car Market Price Vehicle Maintenance Costs

Our study develops a system with primary and over 20 secondary indicators to assess China's new energy vehicle development, focusing on policy, economy, market, and vehicle characteristics. This detailed analysis enhances the study's comprehensiveness and practicality.

Step2 Impact Assessment of Secondary Indicators

To address multicollinearity and redundancy in indicators, this study employs various analytical methods to screen key factors influencing new energy vehicle development, ensuring predictive accuracy.

(1) Correlation analysis

Correlation analysis evaluates relationships between variables, vital for identifying factors affecting new energy vehicle sales. To enhance analysis precision, it's crucial to address indicator homogeneity, ensuring differentiation and avoiding redundancy.

Z-score standardization was applied to unify data analysis benchmarks, enhancing consistency and accuracy in the study.

$$x^{*}=\frac{x-\overline{x}}{\sigma}$$

where $\overline{x}$ is the mean and σ is the standard deviation.

Next, the Spearman rank correlation coefficient was used in this study as a measure of correlation between two variables and its calculation followed the following formula:

$$\rho=\frac{\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})}{\sqrt{\sum_{i=1}^{\mathrm{n}}(\mathrm{x}_i-\overline{x})^2\sum_{i=1}^{n}(\mathrm{y}_i-\overline{y})^2}}$$

where x_i, y_i refers to the specific numerical data of the corresponding feature.

(2) The study measures indicator variability using standard deviation, expressed as follows:

$$\begin{cases}\overline{x}_j=\frac{1}{n}\sum_{i=1}^{n}x_{ij}\\ S_j=\frac{\sum_{i=1}^{n}(x_{ij}-\overline{x}_j)^2}{n-1}\end{cases}$$

(3) Indicator conflictability was calculated using the correlation coefficient as follows:

$$R_j=\sum_{i=1}^{p}(1-r_{ij})$$

A higher correlation coefficient suggests indicator overlap, necessitating reduced weights in allocation.

(4) Information content is estimated by combining indicator variability and conflict, using this formula:

$$C_j=S_j\sum_{i=1}^{P}(1-ri_j)=S_j\times R_j$$

The larger C_j means that the jth indicator plays a greater role in the whole evaluation index system, so we should assign it a larger weight.

Step3 Gray correlation analysis

(1) Characterize the secondary indicator as: $(x_0,x_1,...,x_m)$.

(2) New energy vehicle sales serve as the parent series, representing the key data series of the system behavior, denoted here as x_0 .

(3) Calculate the association coefficient of the subsequence with the corresponding element of the parent sequence :

$$\begin{gathered}\gamma(x_0(k), x_i(k)) = \frac{\Delta\min + \rho\Delta\max}{\Delta_{ik} + \rho\Delta\max} \\ \Delta\min = \min_i \min_k |x_0(k), x_i(k)| \\ \Delta\max = \max_i \max_k |x_0(k), x_i(k)| \\ \Delta_{ik} = |x_0(k), x_i(k)|\end{gathered} \tag{1.1}$$

ρ The resolution coefficient is set in the (0,1) interval, with smaller values indicating greater correlation coefficient differences. In this paper, the resolution coefficient is selected as 0.5.

(4) Calculation of correlation

Information content is estimated by combining indicator variability and conflict, using this formula:

$$r_{oi} = \frac{1}{m}\sum_{k=1}^{m} W_k \zeta_i(k) \tag{1.2}$$

5.3. Solving the Model

Matlab calculated correlation coefficients for 22 indicators and new energy vehicle sales, detailed in Table 5-3.

Table 5-3 Correlation Coefficient Matrix

	Field 1	Field 2	Field 3	Field 4	Field 5	Field 6	Field 7	Field 8
Field 1	1.0	0.9	0.8	0.8	0.8	0.7	0.6	0.6
Field 2	0.9	1.0	0.8	0.8	0.8	0.6	0.5	0.5
Field 3	0.8	0.8	1.0	0.7	0.8	0.5	0.5	0.5
Field 4	0.8	0.7	0.7	1.0	0.5	0.9	0.9	0.9
Field 5	0.8	0.8	0.8	0.5	1.0	0.3	0.2	0.3
Field 6	0.7	0.6	0.5	0.9	0.3	1.0	0.9	0.9
Field 7	0.7	0.5	0.6	0.9	0.3	0.9	1.0	0.7
Field 8	0.7	0.5	0.5	0.9	0.3	0.9	0.7	1.0

Secondary indicators' conflict, variability, and informativeness were calculated, yielding results in Table 5-4.

Table 5-4 Screening Results for Secondary Indicators

Variant	Relatedness
Consumer Spending Index (CPI)	12%
Vehicle Restriction Management	45%

Crude Oil Production	65%
Car Market Price	65%
Private Vehicle Ownership	67%
Government Subsidies for Electric Vehicles	76%
Level of Disposable Income Per Capita	76%
Oil Fuel Costs	76%
Total Road Network Mileage	76%
Maximum Vehicle Mileage	77%
Urbanization Rate	77%
Scale of Electric Vehicle Charging Stations	86%
GDP	87%

Calculation: Conclusions from analysis: GDP per capita, new energy vehicle purchase tax subsidies, new energy vehicle prices, urbanization rate, charging pile holdings, and GDP have strong correlations (>0.6) with new energy vehicle sales. Thus, these 14 indicators will be included in our in-depth analysis and sales forecast model.

6. Problem 2 Modeling and Solving

6.1. ARIMA Model Building and Solving

Our study forecasts China's new energy vehicle industry over the next decade. Due to limited historical data, we employ time series analysis and grey theory forecasting models, offering a specialized and scientific forecasting approach.

Step1 Modeling

ARIMA time-series analysis treats data as random variables following a distribution. With precise modeling and parameterization, it forecasts the future based on historical and current observations, aiding decision-making.

(1) Autoregressive AR Model:

The autoregressive model relies on historical data (p time points before the current value).

$$y_t = \varepsilon_t + \mu + \sum_{i=1}^{q} \gamma_i y_{t-i}$$

(2) MA Model:

MA model reduces random fluctuations in forecasts by summing error terms from the autoregressive model, represented as:

$$y_t = \varepsilon_t + \mu + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

(3) Modified autoregressive moving average (ARIMA) model formed from the traditional method:

By integrating an autoregressive model (AR) with a moving average model (MA), we constructed an autoregressive moving average model, ARIMA(p, q), whose core formulation is described below:

$$\mu + \varepsilon_t + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i}$$

Here we use a combination of these three models thus obtaining the ARIMA(p,d,q) model, which is calculated as shown below:

$$\left(1 - \sum_{i=1}^{p} \phi_i L^i\right)(1-L)^d X_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \varepsilon_t$$

where L is called the lag operator (Lag operator).

Step2 Model solving and testing

In ARIMA (p, d, q) parameterization, determining p and q values is crucial. We use ACF and PACF analysis on differenced data to set p and q. After first-order differencing, sales data shows stability, setting d to 1.

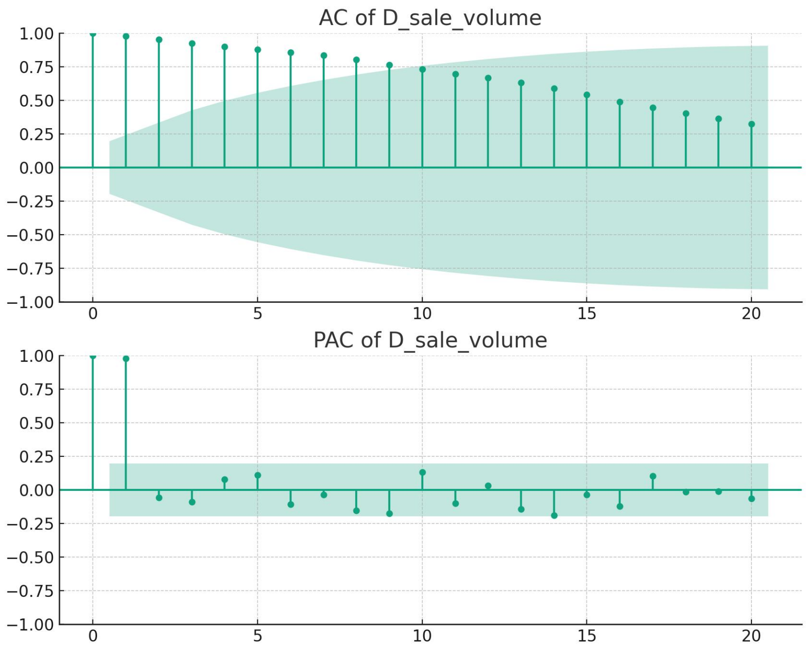

Figure 6-1 ACF and PACF Tests

Table 6-1 BIC Information Guidelines

serial number	ARIMA Combination	BIC
1	ARIMA (2,1,1)	543
2	ARIMA (2,1,0)	524
21	ARIMA (0,1,0)	549.4
22	ARIMA (1,1,0)	549.7

The model combination (2,1,0) with ar.L1 parameter's standard deviation of 0.134 and a p-value below 0.05 performed excellently. Key indicators, including MAE, RMSE, and R2, support its accuracy: MAE = 3.00, RMSE = 5.24, and R2 = 0.87. This model predicts China's new energy electric vehicle development over the next decade (see Table 6-2).

Table 6-2 China's Next Decade New Energy EV Forecast (Unit: 10,000 units)

vintages	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
sales volume	587	1021	1332	1932	3454	4765	7032	9754	10252	11953
retention level	413	590	992	1432	2273	3293	5590	7803	8935	10284

6.2. Establishment and Solution of Gray Prediction Model

Step1 Gray prediction modeling

The GM(1,1) gray forecasting model is chosen for its efficient forecasting ability with limited data. It utilizes a first-order differential equation with 14 variables.

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=\mu$$

Solve using the least squares method:

$$\hat{a}=\left(B^{T}B\right)^{-1}B^{T}Y_{n}$$

Solving the differential equation yields the predictive model.

$$\hat{\chi}^{(1)}\left(\mathrm{k}+1\right)=\left\{\chi^{(0)}\left(1\right)-\mu/a\right\}\mathrm{e}^{-\mathrm{ak}}+\frac{\mu}{\mathrm{a}}$$

Step2 Testing and solving the model

The model's validity is verified using relative error detection and a posteriori difference analysis. It is categorized into four accuracy levels based on C and P, as detailed in Table 6-3.

Table 6-2 Accuracy Levels

hierarchy	C	P
talented	0.35	0.95
eligible (voter etc)	0.50	0.80
barely enough	0.65	0.70
substandard	0.80	0.60

The detailed prediction results are shown in Table 6-3.

Table 6-3 Gray Forecast Results (10,000 units)

vintages	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
sales volume	578	1004	1282	1982	3404	4701	6893	9260	9751	10960

retention level	428	601	987	1427	2373	3528	5309	7702	8585	9644

Conclusion: To forecast China's new energy vehicle industry for the next decade, we combine time series analysis and gray forecasting, presenting key indicators in Table 6-4 and visualizing them in Figure 6-2.

Table 6-4 Combined ARIMA+GM Forecast Results (10,000 units)

particular year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
sales volume	589	1013	1307	1957	3430	4733	6963	9525	10002	11455
retention level	420	595	989	1430	2324	3410	5449	7753	8760	9963

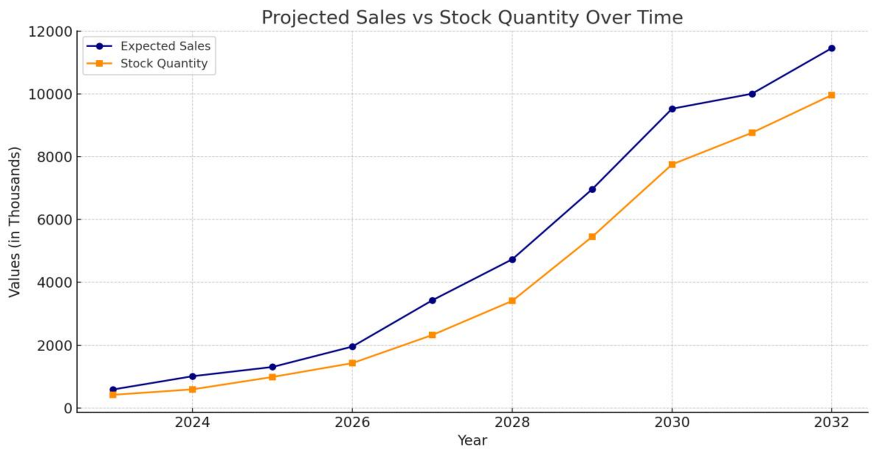

Figure 6-2 Combined Results of ARIMA+GM Predictions

7. Problem 3 Modeling and Solving

7.1. Evolutionary Modeling and Solving

When analyzing the trends of new energy vehicles and the traditional automobile industry, we consider their dynamic game relationship influenced by factors like consumer purchasing power, fuel prices, charging infrastructure, and competition. We use dynamic game theory to simulate industry competition before integrating it with traditional prediction models for more accurate forecast

Step1 Model Assumptions

Under the assumption that all industries pursue a limited ideal, we can set the car buying strategy adopted by consumers as the variable $(p, \overline{p})$ covering the possibility of choosing either a new energy car or a conventional car. Meanwhile, the degree of support from auto parts suppliers for the development of the two vehicle types can be regarded as the strategy $(g, \overline{g})$, which determines whether they promote or do not participate in the progress of their respective industries. At time point t, let the consumer choice proportion of new energy vehicles be $x(t)$ and that of traditional vehicles be $y(t)$, where the value ranges of $x(t)$ and $y(t)$ are both within the closed interval [0,1]. By analyzing the available data, we foresee the future trend $x \to 1$, indicating that new energy vehicles will gradually dominate the market.

The utility value of traditional automobile is set as $\pi_{\bar{p}} = 0$, which reflects its stability and maturity in the market; the utility value of new energy automobile is set as $\pi_p = \pi_{\bar{p}}(x, y) > 0$, which indicates its market potential and growth.

Step2 Evolutionary equilibrium analysis

Based on these assumptions, we can get the power model:

$$\begin{cases} \dot{x} = x(1-x)F(x,y) = x(1-x)(\lambda_1 + \alpha_1 x + \beta_1 y) \\ \dot{y} = y(1-y)F(x,y) = y(1-y)(\lambda_2 + \alpha_2 x + \beta_2 y) \end{cases}$$

Based on the analysis, we derive Jacobi matrices for complex dynamic systems.

$$J = \begin{bmatrix} \partial\dot{x}/\partial x & \partial\dot{x}/\partial y \\ \partial\dot{y}/\partial x & \partial\dot{y}/\partial y \end{bmatrix}$$

$$= \begin{bmatrix} x(1-x)\alpha_1 + (1-2x)(\lambda_1 + \alpha_1 x + \beta_1 y) & x(1-x)\beta_1 \\ y(1-y)\alpha_2 & y(1-y)\beta_2 + (1-2y)(\lambda_2 + \alpha_2 x + \beta_2 y) \end{bmatrix}$$

Step3 Evolutionary Solution Analysis

Scenario 1: Under the assumption that $\lambda_1 > 0$ represents a more desirable development trend, the system will exhibit either a (1,0) or (1,1) outcome pattern. Specifically, when $\lambda_2 + \alpha_2 > 0$ is present, the system will stabilize in a unique state; if $0 > \lambda_2 + \alpha_2 > -\beta_2$ is present, the system may exhibit two different outcomes; and under $-\beta_2 > \lambda_2 + \alpha_2 > \alpha_2$, the system tends to reach a unique (1,0) state.

Model predictions suggest stable growth of new energy vehicles, shifting consumer preference, and traditional auto industry decline. See Figure 7-1 for details.

Scenario 2: Under the assumption of $\lambda_1 + \alpha_1 + \beta_1 < 0$, the evolutionary outcome of the system is influenced by other variables: if $\lambda_2 > 0$, the system tends to reach the state (0,1); if $0 > \lambda_2 > -\beta_2$, two states are possible, namely (0,0) and (0,1); and under the condition of $\lambda_2 + \beta_2 < 0$, the system will stabilize in the unique (0,0) state.

Scenario 2, unlikely in the real market, is excluded from further analysis.

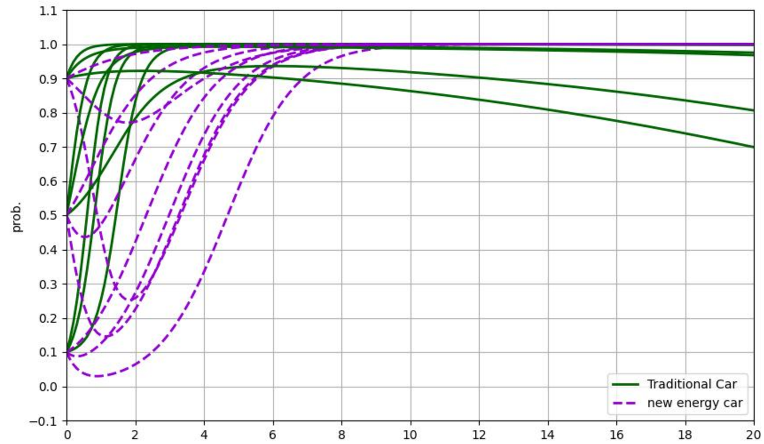

Figure 7-1 Evolutionary Diagram

Conclusion: In scenario 1, new energy vehicles gain an advantage in market competition due to factors like cost and policy support. This leads to a gradual decline in the traditional automobile industry's market share (blue line) and an increase in the market penetration of new energy vehicles (red line approaching 1).

7.2. Predictive Modeling and Solving

Scenario 1's evolutionary game model illustrates how new energy vehicles gradually reduce the traditional automobile industry's market share due to lower costs and policy support. It explains market trends and the industry's reshaping. To predict the traditional automobile industry's challenges and prospects, a comprehensive development prediction model is proposed for richer insights into its future trends

The dataset primarily focuses on key global automotive markets like Germany, the United States, Japan, Italy, South Korea, and China. It includes performance indicators such as vehicle sales, charging facility coverage, market share, manufacturer investments, fuel prices (especially gasoline), aiming for a comprehensive industry analysis.

Step1 Modeling

LSTM is an advanced recurrent neural network architecture that overcomes the gradient dissipation issue in standard RNNs. It excels in long-term time series prediction, preserving historical data and handling multivariate inputs for improved accuracy in capturing long-range temporal dependencies.

(1) First-order lag

In order to accurately predict the value of the y_m indicator for the m period, we can analyze it by combining all available information up to the $m-1$ period.

$$(x_{m-1,1}, x_{m-1,2} \cdots x_{m-1,n}, y_{m-1}) \tag{3.1}$$

Construct a linear model to represent the value of y_m at period m with all the information at period $m-1$

$$y_m = \omega_0 y_{m-1} + \omega_1 x_{m-1,1} + \omega_2 x_{m-1,2} + \cdots + \omega_n x_{m-1,n} + \varepsilon \tag{3.2}$$

Rather than just relying on a single characterization factor y_{m-1} information at period $m-1$, the advantages of multivariate time series are taken advantage of. This includes the ability to synthesize information from multidimensional data when extended to p order lags.

(2) p-order lag can be vectorially represented as:

$$y_m = W_0 Y_{m-i} + W_{m-1} Y_{m-1} + W_{m-2} Y_{m-2} + \cdots + W_{m-p} Y_{m-p} + \varepsilon \tag{3.3}$$

where X_{m-i} represents the feature vector of the previous $i(1 \le i \le p)$ period

$$(x_{m-i,1}, x_{m-i,2}, \cdots, x_{m-i,n}, y_{m-i})^T \tag{3.4}$$

W_{m-i} denotes the coefficients corresponding to the eigenvectors of the previous $i(1 \le i \le p)$ period

$$(\omega_{m-i,1}, \omega_{m-i,2}, \cdots, \omega_{m-i,n}, \omega_{m-i}) \tag{3.5}$$

In this framework, we synthesize all the feature vectors of the previous $m-i$ period, generalized as Y_{m-i} , while ε follows the statistical law of Gaussian distribution. Based on this setup, we can accurately derive the characterization of period m by linear regression method using the feature variables of period $m-p$ and period $m-1$.

We selected the Multivariate Multi-Step (MMS) LSTM model for complex time series data, with optimized parameters shown in Figure 7-2.

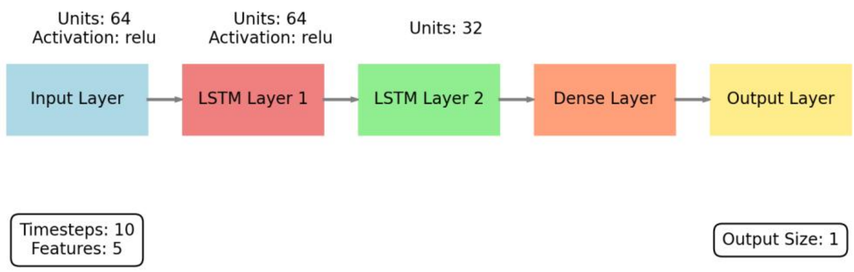

Figure 7-2 Multivariate Multi-Step Modeling

Step2 Model Solving

After an in-depth time-series analysis, we observe a significant shift in global conventional vehicle sales between 2017 and 2025: initially increasing, then declining, with a gradual decrease in market share. Conversely, new energy vehicle sales and their market share consistently rise, notably reaching a turning point around 2022. This aligns with global environmental concerns, policy support, and the push for new energy vehicles. For specific data and trends, refer to Table 7-2 and Figure 7-3.

Table 7-2 Conventional Automotive Industry Development Projections

Year	C-C	C-P-O	N-E-V	P-N-E-V	P-C-V

2017	98642	44970	9129	8.5%	91.5%
2018	138892	60345	14857	9.7%	90.3%
2019	140921	84450	26549	15.9%	84.2%
2020	154392	105267	29987	16.3%	83.7%
2021	165600	118803	33764	17.0%	83.1%
2022	187900	150774	46229	19.7%	80.3%
2023	163300	192795	88982	35.3%	64.7%
2024	158700	246789	110394	41.0%	59.0%
2025	149500	275325	137297	47.9%	52.1%

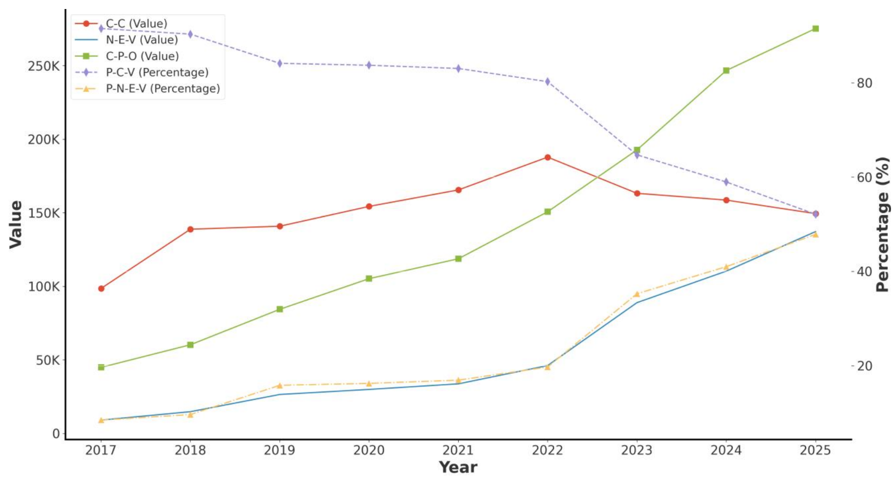

Figure 7-3 Traditional Automotive Industry Trends

Conclusion: Using an evolutionary game model, this study predicts that new energy vehicles will gain momentum due to policy support and cost advantages. The absence of "Scenario 2" in the model highlights the profound impact of electric vehicles on the traditional fuel automobile industry. Additionally, the time series forecasting model quantifies this impact, improving predictions of future industry trends.

8. Problem 4 Modeling and Solving

8.1. Modeling

This question aims to analyze the impact of U.S.-led international sanctions on China's new energy vehicle industry. These sanctions involve measures like chip export restrictions, investment limitations, and increased tariffs. Their effects include supply chain disruptions, component shortages, export declines, higher production costs, and reduced sales. The study focuses on U.S. sanctions as an example.

Step1 Selection of Model-related Variables

This research model considers factors such as exchange rate effects on Chinese new energy vehicle parts imports, foreign investment constraints, and tariff impacts in the U.S., Germany, and Japan. These factors may reduce China's new energy vehicle international sales. Refer to Exhibit 8-1 for details.

Table 8-1 Boycott Policy Related Data

vintages	sales volume (million vehicles)	Japanese tariffs	US tariffs	German tariffs	Imports (billions)	Foreign investment (billions)	exchange rates
2013	1.8	3.8	3.0	2.3	1538	6271	6.8
2014	7.5	3.8	3.0	2.3	2380	7367	6.8
2015	33.1	2.3	2.9	2.2	2971	7602	6.5
2016	50.7	3.8	2.9	2.8	3174	7152	6.3
2017	77.7	3.5	2.8	2.7	3287	7353	6.2
2018	125.6	3.5	2.8	2.5	3777	7353	6.1
2019	120.6	3.7	3.4	2.5	3294	7864	6.2
2020	136.7	3.8	3.3	2.5	3478	8369	6.6
2021	165.2	5.9	8.7	2.6	3968	8847	6.8

Step2 Modeling

Understand the data with scatter plots, construct regression models (including log-transformed forms) for in-depth analysis, and test for statistical validity by examining heteroskedasticity and multicollinearity.

The logarithmic form model, calculated as follows:

$$\begin{aligned} \ln Y_1 &= \beta_0 + \beta_1 \ln(x_1) + \beta_2 \ln(x_2) + \beta_3 \ln(x_3) \\ &+ \beta_4 \ln(x_4) + \beta_5 \ln(x_5) + \beta_6 \ln(x_6) + \mu \end{aligned} \tag{4.1}$$

Multiple regression model, calculated as follows:

$$\begin{aligned} Y_1 &= \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \\ &+ \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \mu \end{aligned} \tag{4.2}$$

8.2. Solving the Model

Utilized Eviews for modeling and analysis, with the ordinary multiple linear regression model outperforming the logarithmic form. Chosen for subsequent model construction and reliability testing. See Exhibit 8-2 for details.

Table 8-2 Results of Multiple Linear Regression Models

Variable	Std. Error	Confficient	t-Statistic	Prob.
C	1014.256	238.105	0.23476	0.836
X1	149.755	-66.018	-0.44084	0.702
X2	0.05751	0.02718	0.47272	0.683
X3	21.311	-13.1458	-0.61684	0.600
X4	46.178	49.5869	1.07382	0.395
X5	136.566	-86.6746	-0.63467	0.591
X6	0.07326	0.04453	0.60781	0.605
S.D. dependent var	59.829	Mean dependent var		79.8778

Durbin-Watson stat	2.2015	R-squared	0.88480
F-statistic	1.56000	Adjusted R^2	0.83917
Prob of F-statistic	0.01733		

The results of the model showed a modified R^2 of 0.839 and an F-test value of 1.56 ($p<0.05$) indicating that the model is statistically significant. T The calculation formula is as follows:

$$VIF = \frac{1}{1-R^2} \quad Tolerance = 1 - R^2 \tag{4.3}$$

Knot analysis results: VIF = 8.620 (below the threshold of 10), Tolerance = 0.116 (above the limit of 0.1), indicating no multicollinearity issues. White test: F-statistic = 1.04732, p-value = 0.56400, confirming no heteroskedasticity..

Table 8-3 White's Heteroskedasticity Check

Explained SS Ratio	0.35521	Prob. Chi-Square(6)	**0.999**
Observed R^2	6.82711	Prob. F(6,2)	**0.564**
F-statistic	1.04732	Prob. Chi-Square(6)	**0.337**

Variable	t-Statistic	Std. Error	Confficient	Prob.
C	-0.30511	7251.86	-2212.61	**0.789**
X1^2	0.30197	156.143	47.150	**0.791**
X2^2	0.53704	4.32E-05	2.32E-05	**0.645**
...	...	...	...	...
X6^2	-0.36409	0.00016	-5.71E-05	**0.751**

As shown in Figure 8-1 below, the residuals (Residual), actuals (Actual), and fitted values (Fitted) of the model are visualized.

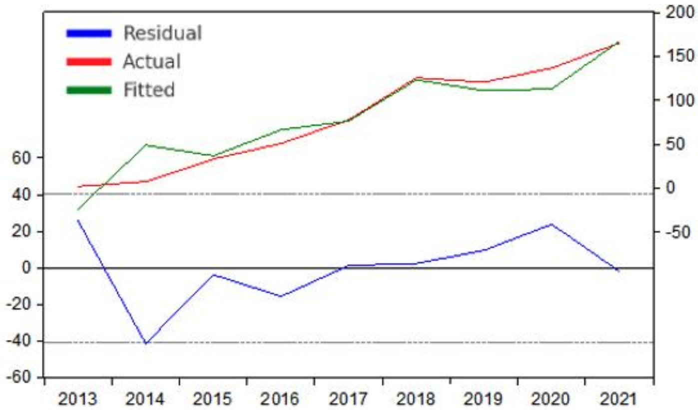

Figure 8-1 Visualization of Regression Effects

The final regression model is shown below:

$$\begin{aligned} Y &= 238.105 - 66.018 * X_1 + 0.02718 * X_2 - 13.1458 * X_3 \\ &+ 49.5869 * X_4 - 86.6746 * X_5 + 0.5553 * X_6 \end{aligned} \tag{4.4}$$

Conclusion: Exchange rate is the most significant barrier to China's new energy vehicles. US and German tariffs also hinder, with Germany having a stronger impact. Foreign investment, though positive, shows a weak effect and may hinder future development.

9. Problem 5 Modeling and Solving

9.1. Modeling

Electrification has several key environmental indicators: energy efficiency gains, reduced carbon emissions, lower urban noise pollution, and sustainable resource utilization, especially battery recycling. These dimensions assess EV electrification's environmental benefits.

Therefore, an innovative penalty factor is used here to differentially assess the carbon emission impacts of new energy EV electrification in different cities, aiming to provide a customized environmental benefit analysis for policy formulation.

Step1 Calculation of Penalty Factor

Penalty factors for carbon emissions are derived from variables like household size and vehicle ownership (see Table 9-1).

Table 9-1 Variable Descriptions

variant	Variable Description	Numerical Interval (math.)	Unit of Measure
E_{ev}	Penetration of New Energy Electric Vehicles	0-1	%
$1-E_{ev}$	Prevalence of Conventional Fuel Vehicles	0-1	%
E_{eb}	Percentage of Electric Public Transportation	0-1	%
$E_{r\ ecycle}$	Recycling Rates for New Energy Electric Vehicles	0-1	%
$R_{r\ ecycle}$	Share of Renewable Energy in Electrified Systems	0-1	%
R_{noise}	New Energy Trams Reduce Noise Emissions Compared to Conventional Vehicles	5-20	dB/Year
R_{co2}	New Energy Trams Reduce CO2 Emissions Compared to Conventional Vehicles	1-5	Tons/Year
H	Average Household Size	1-5	Persons/Household
C	Number of Electric Vehicles Per Household	1-3	Vehicles/Household
M	Miles Traveled Per Vehicle	1k-10k	Kilometers/Year

Higher correlation reduced conflict in assessment. More details on model construction to follow.

$$\begin{cases} \overline{x_j} = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \\ S_i = \sqrt{\frac{\sum_{i=1}^{1}(x_{ij} - \overline{x_j})^2}{n-1}} \end{cases}$$

Higher indicator variability means more information; these should be given higher weights for accuracy.

$$R_j = \sum_{i=1}^{p}(1 - r_{ij})$$

High indicator correlation means redundant information; we'll reduce their weight for system diversity.

$$C_j = S_{ij} = S_j * R_j = p_1 - r_{rj}$$

The results of the assignment are shown in Table 9-2 below

$$W_j = \frac{C_j}{\sum_{j=1}^{p} C_j}$$

Table 9-2 Assignment of Weights

variant	weights	variant	weights
W1	0.10	W6	0.20
W2	0.05	W7	0.05
W3	0.15	W8	0.05
W4	0.15	W9	0.10
W5	0.10	W10	0.05

Determination of parameters and calculation of effect values:

$$Effect_i = \frac{P_i - P_{i,new}}{P_{i,\max} - P_{i,\min}} (i = 1, 2, \cdots, 10) \tag{5.4}$$

Thus, the penalty factor S for each city can be expressed as follows:

$$S = \sum_{i=1}^{11} W_i \times \frac{Effect_i}{MaxEffect_i} \tag{5.5}$$

Step2 Model Construction

We use an advanced model for energy consumption and emissions prediction in a city of one million, considering regional fuel mix and vehicle phase-out rules.

$$VP_{j,p} = \sum_a NR_{j,y-a} \times \varphi_{a,j}(y)$$

$$\varphi_{a,j}(y) = \frac{n_{a,j}(y+a)}{n_{0,j}(y)} \tag{5.6}$$

Average annual distance traveled is a key indicator for energy consumption and carbon emissions. The following equations were used for the specific calculations:

$$EC_y = S * \sum_i \sum_j VP_{i,j,y} \times VEC_{i,j,y} \times VKT_{i,j,y}$$

$$CE_y = \sum_i EC_{i,y} \times EF_{i,y} \tag{5.7}$$

$$\left(S = \sum_{i=1}^{11} W_i \times \frac{Effect_i}{MaxEffect_i} \right)$$

9.2. Solving the Model

We collected data and used recognized proxies when necessary.Specific data details and their proxy values are listed in Exhibit 9-3.

Table 9-3 Data Indicators

Norm	Digital	Unit of Measure
Vehicle ownership ratio	0.3	%
Electric Vehicle Penetration	20	%
Electric Vehicle Scrap Disposal Rate	0.9	%
Percentage of Electric Buses	17	%
Percentage of Electrified Vehicles	0.3	%
Noise Reduction Index	16	db
Annual Vehicle Distance Traveled	6400	Km
Emission Indicators	1.5	t
Average Number of Members per Household	3.0	Persons/Household
Total Urban Population Size	100	All the People
Oil Fuel	2936	g/kg
Diesel Fuel	3152	g/kg
All-electric Power	418	g/kg
Gas Powered	216	g/m^3
Hydrogen Fuel	15000	g/kg

In order to gain insights into the ecological impacts of the promotion of new energy electric vehicles (EVs) under short- and medium- to long-term countermeasures, especially in terms of carbon emission indicators, this study constructed an integrated model. In order to present these results more intuitively, a detailed visualization of the analysis is provided in Figure 9-1.

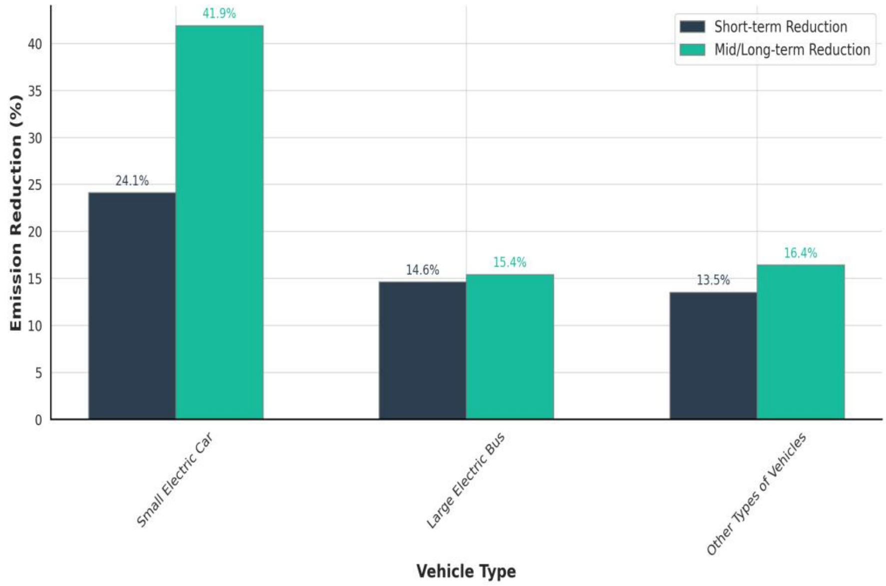

Figure 9-1 Visualizing the Impact of Different Policies

Conclusion: Our innovative model assesses the environmental impact of electrifying new energy vehicles, showing significant CO2 reduction potential for electric sedans, while medium- and large-sized electric buses have minor changes due to existing electrification. Overall, electrification positively reduces carbon emissions, contributing to environmental protection.

10. Problem 6 Solving

Dear Citizens:

We have some exciting news to share with you about the incredible potential of new energy electric vehicles (NEVs) and the contributions of the electric vehicle (EV) industry worldwide. Our recent study, driven by innovative modeling and rigorous analysis, uncovers the transformative impact of NEVs on our environment.

Our research reveals that the electrification of NEVs, especially electric sedans, has the power to significantly reduce CO2 emissions. This means cleaner air, healthier environments, and a substantial step towards addressing global warming. The possibilities for positive change are immense.

But there's more to the story. Electric buses, while showing stable emissions reduction due to existing electrification efforts, play a crucial role in sustainable urban mobility. They make our cities quieter, reduce noise pollution, and enhance urban life.

What's remarkable is that these advancements are not confined to one country or region; they are a global movement. Countries worldwide, including Germany, the United States, Japan, Italy, South Korea, and China, are recognizing the importance of EVs and taking steps to support their growth. The global automotive community is uniting to embrace electrification and transform transportation.

We stand at the forefront of a revolution. Electrification is not just about reducing emissions; it's about reshaping our future for the better. It's about cleaner cities, quieter streets, and a healthier planet for us and future generations.

So, what can you do to be part of this change? Consider adopting an NEV for your daily commute. Support policies and initiatives that promote the growth of the electric vehicle industry. Spread the word about the benefits of electrification to your friends and family.

Together, we can drive the transition to a cleaner, greener future. Electrification is not just a technological advancement; it's a global movement towards a more sustainable and environmentally friendly world.

Thank you for your attention, and let's embrace the future of electric mobility together.

Sincerely,
XXX

11. Evaluation, Improvement and Generalization of Models

◆ **Analysis of the Strengths and Weaknesses of the Model**

Modeling Advantages:

(1) Comprehensive and detailed analysis: The model covers policy, economy, market, and vehicle factors, allowing in-depth analysis.

(2) Strong time series and forecasting capabilities, including ARIMA and flexible gray forecasting models for diverse data conditions.

(3) Comprehensive and dynamic analysis, combining different models to enhance accuracy, adaptability to changing markets.

Model Disadvantages:

Complexity and data sensitivity: Requires expertise and high-quality data due to indicator volume and analysis complexity.

◆ **Improvements to the Model**

Enhance data collection, cleaning, and validation processes to ensure the accuracy and currency of the data. Utilize interpolation techniques for handling missing values and employ data standardization methods to enhance overall data quality.

◆ **Extension of the Model**

When constructing the model, we prioritize simplicity and adaptability. We simplify by optimizing data and indicators for ease of use. Adaptability means adjusting to market and policy changes, ensuring the model remains effective in a dynamic real-world environment.

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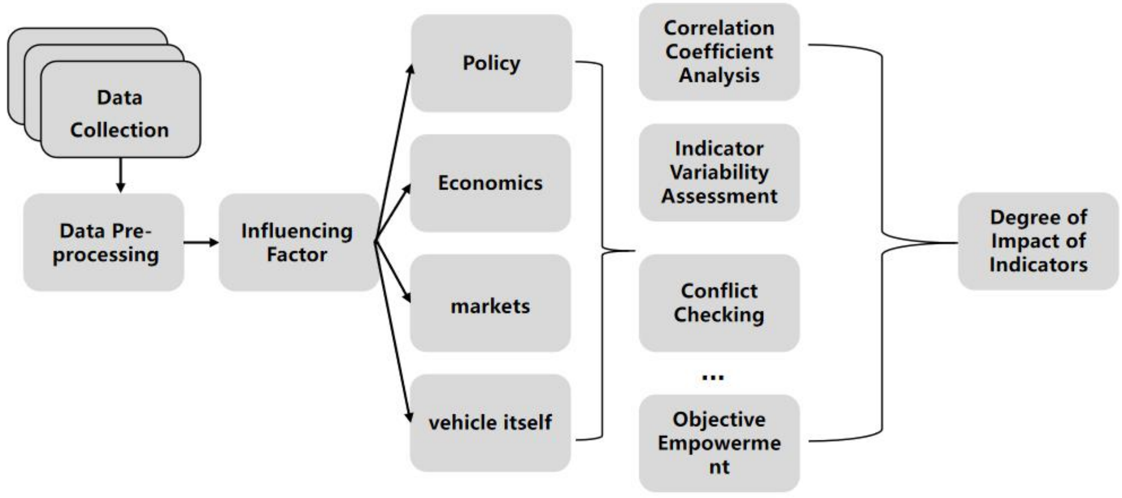
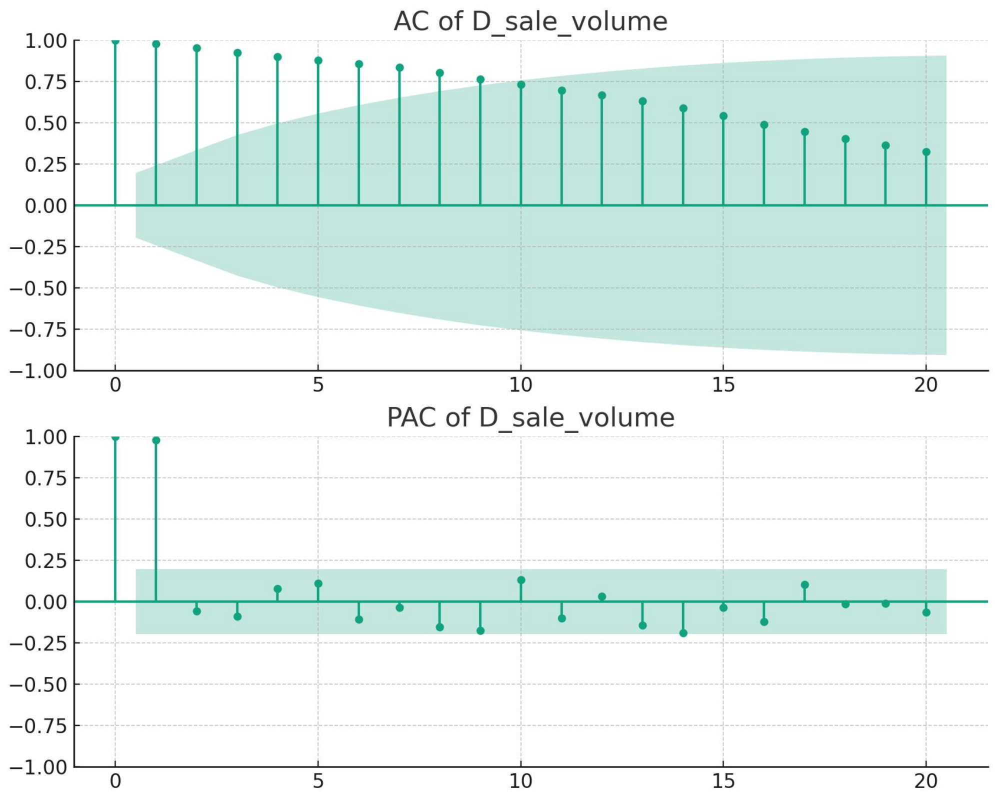
13. Appendice

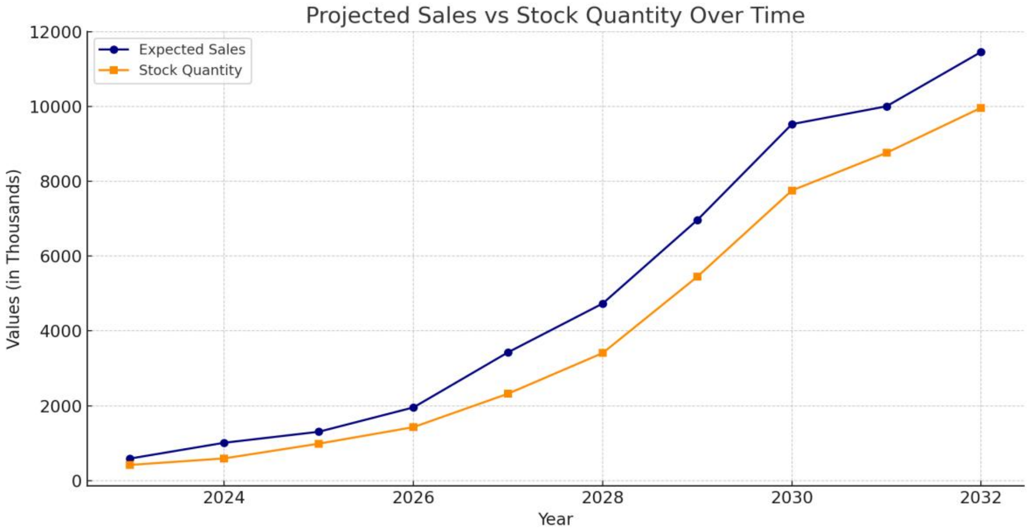
1. Problem 1 Solution Idea Flowchart



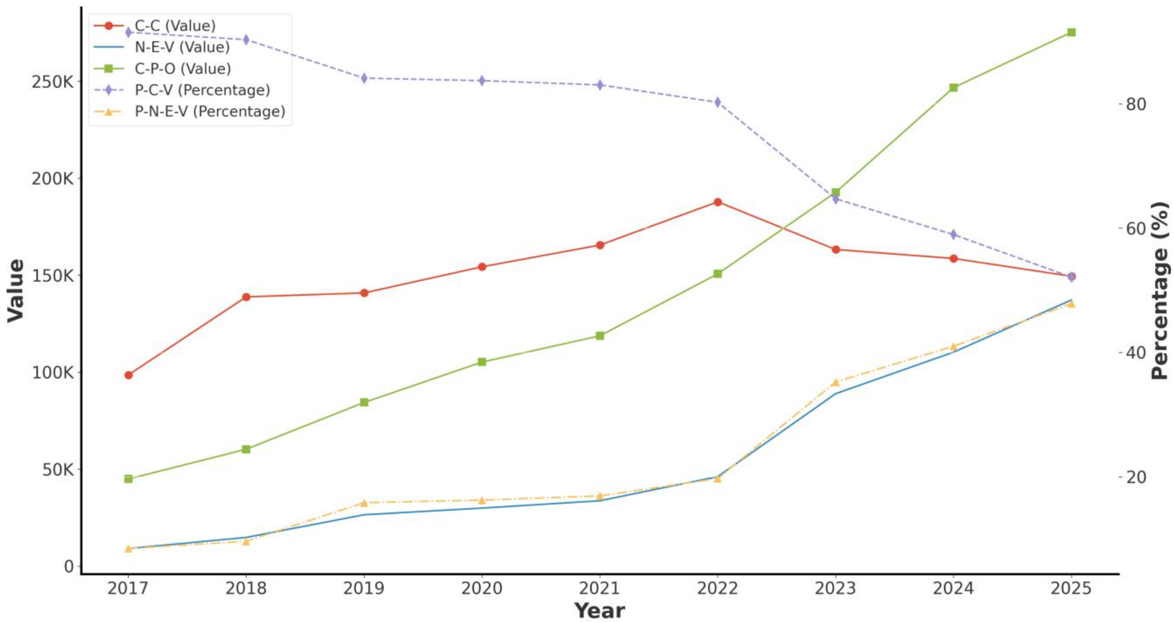
2. ACF and PACF Tests



3. ARIMA+GM Predicts Combined Results



4. Traditional Automobile Industry Development Trend Chart



Appendix 2										
1.Forecast of China's New Energy Electric Vehicle Development in the Next Ten Years										
particular year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
sales volume	587	1021	1332	1932	3454	4765	7032	9754	10252	11953
retention level	413	590	992	1432	2273	3293	5590	7803	8935	10284

2.Environmental Impacts of Electrification Under Different Strategies

Vehicle Type / Deal	Small Electric Vehicles	Large Electric Buses	Other Types of Vehicles
Short-term emission reductions	24.1%	14.6%	13.5%
Medium- and long-term emission reductions	41.9%	15.4%	16.4%