Team Number:	apmcm2303763
Problem Chosen:	C

2023 APMCM summary sheet

This paper addresses multiple issues pertaining to the development and impact of new energy vehicles in China.

In the first problem, patent numbers, subsidies, per capita disposable income, and charging station quantities from 2010 to 2022 are collected and used as influencing factors. The sales volume of new energy vehicles is the dependent variable.A multiple regression equation is established, with regression coefficients indicating the importance of each factor. The order of importance is determined as subsidies, patents, per capita income, and charging station growth rate.

In the second problem, seven indicators representing the electric vehicle industry's development, including market penetration rate, number of charging stations, and production volume, are identified. Time series analysis using ARIMA models is conducted on market penetration rate and sales volume, identified as pivotal development indicators.

The third problem involves data collection on new energy and traditional vehicles, employing the least squares method for analysis.A population competition model predicts future trends in the ownership and sales of new energy and traditional vehicles, validated against original data.

For the fourth problem, the export volume of new energy vehicles is selected as the policy-influenced indicator. Historical restrictions from major market countries on China's new energy development are investigated using a time series approach. A DID model is employed to ascertain the strong negative correlation between foreign policy implementations and China's new energy vehicle exports.

Lastly, the fifth problem entails establishing a polynomial model based on urban car statistics to derive data for a city of one million inhabitants. This data is used to construct a model assessing the impact of vehicle electrification on the environment, considering factors like gasoline emissions' CO2 coefficients.

Keywords: New Energy Vehicles   Regression Analysis   Time Series   Policy Impact   Environmental Impact   Urban Car Statistics

Contents

I. Introduction

1.1 Background

In recent years, countries around the world have been calling for low-carbon and environmental protection. Only by developing clean energy and new energy industries can we promote the vigorous development of new energy in the world. In the face of global greenhouse warming and worsening environmental pollution, fuel emissions from traditional vehicles have become the main cause of greenhouse warming. In such a general environment, new energy vehicles,especially electric vehicles(EV), emerged as the times require.

With the development of the science and technology, China has continuously increased its requirements for vehicular exhaust emission. New energy electric vehicles(NEEVs), as a new, eco-friendly, and efficient industry, conforms to the concept of green energy and can effectively reduce environmental pollution.[1] So the development and impact of new energy electric vehicles are the two topics people more and more concerned on.

But the development of new energy electric vehicles is affected by factors from various aspects.They may from the government policies,production technology, infrastructures, value for money compared to substitute goods,and so on.Identifying the factors that affect the development of new energy electric vehicles, making reasonable judgments on the importance of each factor, and predicting future development trends and social impacts are urgent issues that need to be solved at the moment.

1.2 Problem Restatement

Taking into account the background information and restricted constraints identified in the problem statement, we need to settle the following questions:

- **Problem 1**

  Figure out the main influencing factors on the development of new energy electric vehicles, establish corresponding mathematical models, and explain how the factors affect the development of new energy electric vehicles in China.

  具体是怎么做的，
  如何找到特征之间的关系；

- **Problem 2**

  Choose appropriate influencing factors that can reflect the development of China's new energy electric vehicles, select the indicators which affect the chosen factors and collect more detailed data of them, establish rational mathematical models, and forecast the development of new energy electric vehicles in China in the next ten years.

预测未来十年的趋势，可以用时序模型来做

⋆ **Problem 3**

Based on the findings of problem 1 and 2, and extend Chinese model to the world, collect required data and improve the model, analyze the impact of the new energy electric vehicle industry on the traditional energy vehicle industry.

⋆ **Problem 4**

In order to limit the rapid development of new energy electric vehicles in China, some countries have introduced policies to boycott Chinese new energy vehicles, establish a model that reflects the impact of these policies on the development of new energy electric vehicles in China.

⋆ **Problem 5**

Analyze the influences of the urban new energy electric vehicles on the ecological environment, plug in a city of one million people and get the result.

⋆ **Problem 6**

According to the model and conclusion of the previous question, write an open letter to propagandize the benefits of new energy electric vehicles and the contribution of their industry to countries around the world.

II. Assumptions and Justifications

Assumption 1

Assuming that the data obtained from the search has a certain degree of credibility and rationality.

Assumption 2

Assuming in the optimal species competition differential equation model, when new energy vehicles exist independently, they follow the logistic pattern of population change.

Assumption 3

Assuming that the new energy electric vehicles in the optimal species competition differential equation model are treated as pure electric vehicles.

Assumption 4

Assuming that all new energy electric vehicles in problem 5 are purely electric.

Assumption 5

Assume that urban vehicles in problem 5 do not include trucks, and all fuel vehicles use gasoline as energy consumption.

III. Notations

Symbol	Description
u_n	The policy subsidy amount for the year n
$u_n^{'}$	Revised policy subsidy indicators
z_n	The number of relevant patents for the year n
k_n	The median personal disposable income for the year n
c_n	The number of electric vehicle charging stations as of year n
$c_n^{'}$	The growth rate of charging stations in year n
y	Objective function
n	years
η	market penetration
$y^{'}$	The potential number of the entire market

IV. Main Factors : What Affect the Development of NEEVs?

4.1 Data Description

4.1.1 *Data Collection and Pre-processing*

In order to analyze the main factors that affect the development of new energy electric vehicles in China, relevant data sets need to be collected. Owing to various statistical departments associated with distinct elements, the Table 1 below illustrates the origins of the data sets utilized in this chapter alongside the explanations of variables.

Table 1 Data source

Production and sales	Ministry of Industry and Information Technology of China
Government subsidy allocation	Ministry of Industry and Information Technology of China
Number of related patent applications	Autopat website
Personal annual disposable income (median)	National Bureau of Statistics
Number of charging piles in stock	China Electric Vehicle Charging Infrastructure Promotion Alliance

Since most of the data obtained in the preliminary work is not in a form that can be directly used, these data should receive some preliminary processing.

In order to eliminate the influence of different dimensions of each set of data and facilitate the construction of a multivariate regression model, data for each variable should be normalized. Due to the relatively stable nature of the data without extreme outliers in its maximum and minimum values, this paper utilizes min-max normalization to process the data. It can be represented by the following formula:

$$x' = \frac{x - min(x)}{max(x) - min(x)} \tag{1}$$

x is a specific index of the variable, $x' \in [0, 1]$, $max(x)$ and $min(x)$ respectively represent the maximum and minimum values of the sample data.The variables mentioned below are all normalized by default.

4.2 New Energy Electric Vehicle Development Model

4.2.1 *Influencing Factors and Index Setting*

Unless otherwise specified, the following data defaults to years as the time series.

Comprehensive analysis of research reports from major institutions and existing research in this field, Sales of new energy electric vehicles (y) are considered a mainly indicator of development. It will be used as the dependent variable in the multiple linear regression analysis in this chapter.

Combined with practical considerations and according to relevant research [2, 3] , the main factors affecting the development of NEEVs include subsidy policy provided by the state (u_n) , number of related patents successfully applied for during this period (z_n) , citizens' personal disposable income (k_n) , number of charging piles nationwide (c_n) .

It should be noted that the personal disposable income here is the median, not the average. For the median represents the middle value when all incomes are arranged in ascending order, offering a more robust measure that is not as heavily influenced by the extreme values.

4.2.2 *Multiple Linear Regression Model*

Establish a multiple linear regression model between each factor and the sales:

$$y = \beta_1 + \beta_2 z_n + \beta_3 u_n^{'} + \beta_4 k_n + \beta_5 c_n^{'} \tag{2}$$

Among them, The growth rate of charging stations in year n $c_n^{'}$ is represented by the following formula:

$$c_n^{'} = \frac{c_n - c_{n-1}}{c_n} \tag{3}$$

The revised policy subsidy indicators $u_n^{'}$ equals to $u_n^{\frac{3}{2}}$

4.2.3 *Results*

Use the regress function in Matlab to establish a multiple linear regression model and obtain the estimated value of the regression coefficient β,the regression model can be expressed as:

$$y = -0.010 + 0.491 z_n + 1.192 u_n^{'} + 0.319 k_n + 0.012 c_n^{'} \tag{4}$$

Table 2 Model Summary

R-squared	F-test	p-value	Standard Estimate Error
0.9994	423.6054	0.0364	0.0004

The model summary shows that the R-square of the model is 0.9994,the large F value and the p value of 0.0364 (less than 0.05) indicate that the model is significant overall and the regression coefficient is credible.The overall fitting effect is good. The multiple linear regression fitting plot and residual plot are shown below:

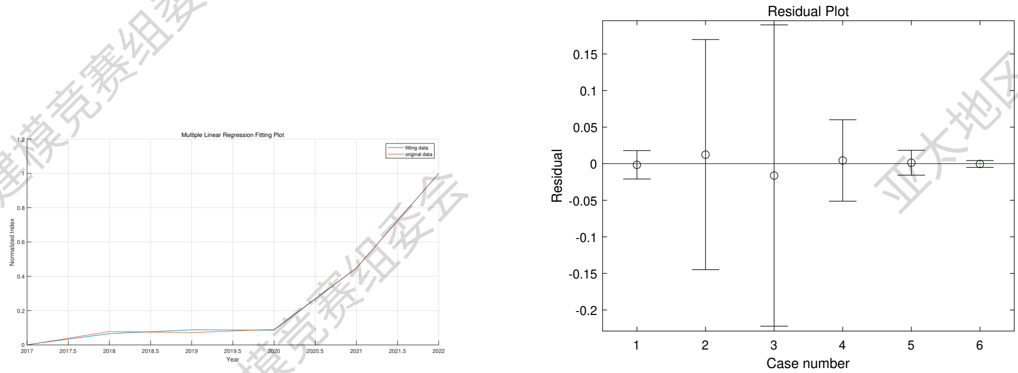


Figure 1 Multiple linear regression fitting plot and residual plot

V. What Will the NEEVs Be In the Next 10 Years?

5.1 The Data

5.1.1 *Data Collection and Data Pre-processing*

In this chapter, the sales data of NEEVs collected in the previous question are continued to be used. The market penetration data was gathered from China's Ministry of Industry and Information Technology and supplemented by information sourced from the China Association of Automobile Manufacturers.

Since it is observed that the initial data has exponential growth properties (refer to the left pictures in Figures 2 and 3), we perform logarithmic processing on the original data. The data after logarithmic processing is more stable and can make the time series more stable (refer to the pictures on the right of Figures 2 and 3). These data are now prepared and ready to be used for model fitting.

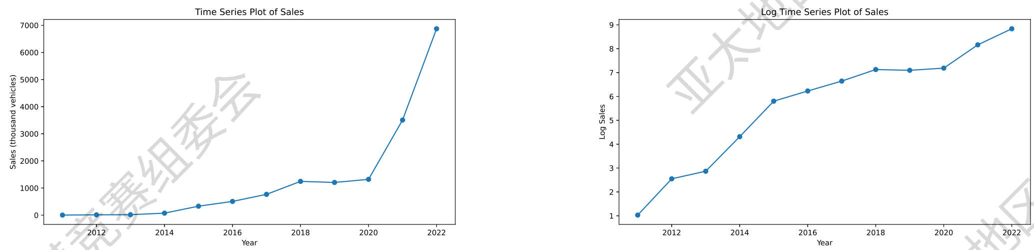


Figure 2 Sales time series plot and the plot with Log Transformation

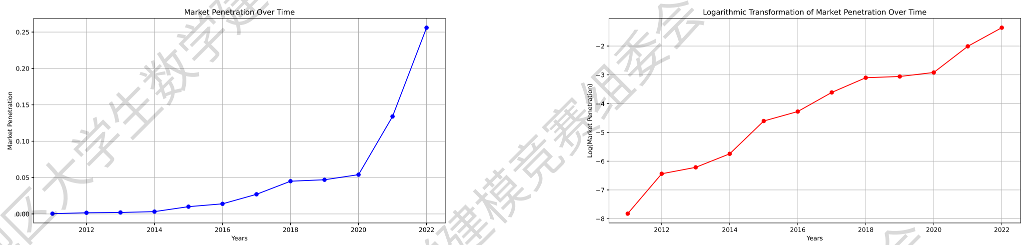


Figure 3 Market penetration rate time series plot and the plot with Log Transformation

5.2 Forecast model for the development of NEEVs in China

ARIMA model is chosen due to its capability in handling time series data exhibiting temporal dependencies and trends. This model is particularly suitable for our dataset as it can account for the temporal nature and potential autocorrelation present in the variables, providing a robust framework for time series analysis and forecasting.

The following diagram (Figure 4) illustrates the step-by-step process used to solve the problem discussed in this article.

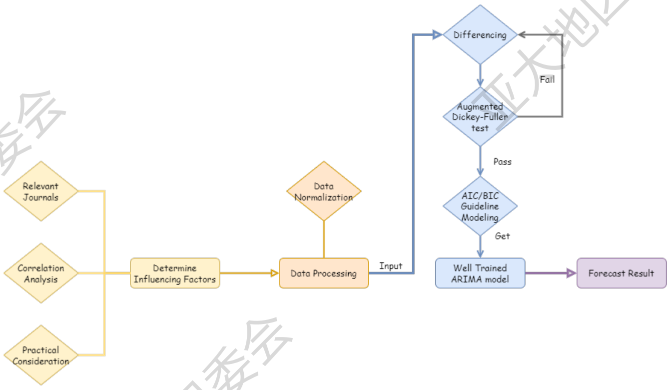


Figure 4 Step flow chart

5.2.1 *Influencing Factors*

Regarding the selection of influencing factors, this paper first conducts a correlation test on the influencing factors selected in problem 1 and some factors that are objectively believed to have strong relevance to the development of new energy electric vehicles.

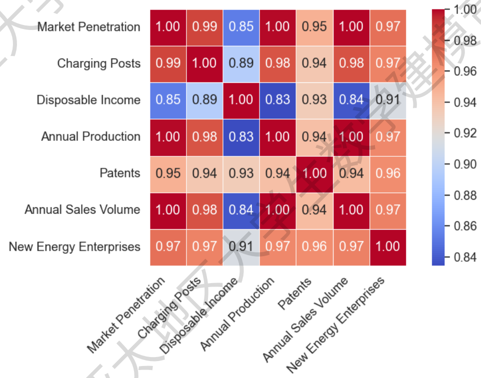


Figure 5 Correlation matrix between feature variables

As can be seen from the above figure, the correlation between feature variables is very strong. This also shows that some feature variables provide similar information to other variables. Therefore, based on the selection rate of influencing factors in mainstream research reports on the new energy electric vehicle industry, this article selects sales volume and market penetration as indicators to reflect the development of new energy electric vehicles in China.

Here comes the conception of market penetration(η). It is related to sales data for the year(y),and the potential sales data of the automobile market that year(y'). The formula is as follows:

$$\eta = \frac{y}{y'} \times 100\% \tag{5}$$

5.2.2 *ARIMA time series forecasting*

The ARIMA (Autoregressive Integrated Moving Average) model is a widely used time series analysis technique for forecasting future values based on historical data patterns. The mathematical formula of an ARIMA(p, d, q) model is represented as:

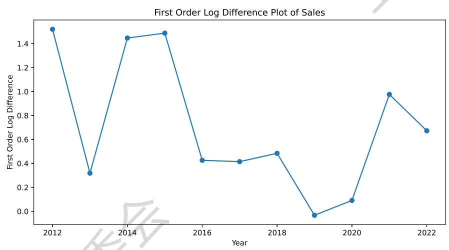
$$(1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_2 B^p)(1 - B)^d X_t = (1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q) Z_t \tag{6}$$

where X_t is the time series data, B is the back shift operator, ϕ_i and θ_i are the autoregressive and moving average parameters, p is the autoregressive order, d is the differencing degree, and q is the moving average order.

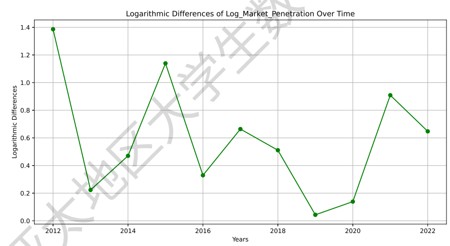
In order to build an ARIMA model, it is necessary to select appropriate parameters p, q, d.

⋆ **Step 1:** Differential processing and ADF test

Differencing aims to transform a non-stationary time series into a stationary one for better model fitting. Perform Augmented Dickey-Fuller (ADF) test after each differencing. If p-value is ¡ 0.05, the test is successful. If not, continue differencing until p-value ¡ 0.05. After first differencing, sales volume remains non-stationary with a p-value ¿ 0.05.



(a) First difference of logarithm of sales volume



(b) First difference of logarithm of market penetration

Figure 6 First order difference of logarithmic time series

Then perform the second-order difference on the sales volume, and the p value is less than 0.05.

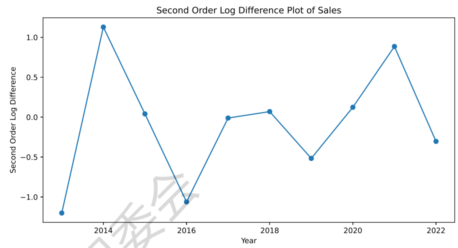


Figure 7 Second order difference of logarithmic time series of sales volume

The data is as follows:

Table 3 ADF statistics and p-value

	sales volume		market penetration	
	ADF statistics	**p-value**	**ADF statistics**	**p-value**
first-order differencing	-1.7733	0.3938	-4.4307	0.0002
second-order differencing	-3.2121	0.0193		

★ **Step 2:** Determination of p and q

Due to the limited amount of data, accurately determining the orders p and q of the ARIMA model from the autocorrelation function (ACF) and partial autocorrelation function (PACF) can be quite challenging. Hence, the use of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) is adopted to ascertain the values of p and q.

AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) are statistical measures used for model selection among different candidate models.

AIC balances a model's goodness of fit with its complexity to find the best trade-off between them. A lower AIC value indicates a better model. It's calculated as $2k - 2\ln(\widehat{L})$, where k is the number of model parameters and $\widehat{L}$ is the maximum likelihood function value for the model.

Similarly, BIC also aids in model selection but penalizes complex models more. It aims to choose simpler models by giving a heavier penalty for complexity than AIC. Lower BIC values denote better models. The BIC formula is $-2\ln(\widehat{L}) + k\ln(n)$, where n is the sample size.

This paper explored various combinations of different p and q values, calculating their corresponding AIC and BIC values. Ultimately, it pinpointed specific p and q combinations that resulted in the lowest AIC or BIC values.

For sales volume, two sets of p and q values meet the criteria: $p = 3$, $q = 1$ and $p = 0$, $q = 1$ are both valid. For market penetration, there are also two sets: $p = 3$, $q = 0$ and $p = 3$, $q = 1$, both meeting the conditions.

Now, the appropriate parameters p, d, and q have been determined.

5.2.3 *Results*

The ARIMA(3,2,1) and ARIMA(0,2,1) models are employed to fit and forecast sales data for the forthcoming decade. Simultaneously, the ARIMA(3,1,0) and ARIMA(3,1,1) models are utilized for fitting and forecasting market penetration.

Table 4 Forecast of the development of NEEVs in China in the next 10 years

	sales volume(000 vehicles)		market penetration	
year	ARIMA(3,2,1)	ARIMA(0,2,1)	ARIMA(3,1,0)	ARIMA(3,1,1)
2023	9034.13	10060.69	0.4148	0.3946
2024	10543.80	13249.39	0.4625	0.4219
2025	13200.22	16438.08	0.4862	0.4537
2026	16383.31	19626.78	0.5367	0.5223
2027	18609.43	22815.47	0.6170	0.5917
2028	20462.89	26004.17	0.6932	0.6293
2029	23134.30	29192.86	0.7415	0.6502
2030	26070.49	32381.56	0.7712	0.6821
2031	28315.21	35570.25	0.8058	0.7243
2032	30379.75	38758.95	0.8540	0.7585

Based on the projected data, the sales volume over the next decade is anticipated to surge from 9 to 10 million to a range of 30.3 to 38.7 million units. This represents a growth in sales data by a factor of 3.36 to 3.85 over the ten-year period.

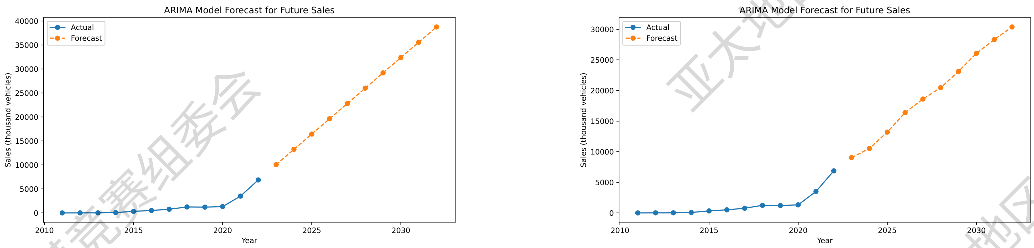


Figure 8 Sales forecast result of p=0,q=1(left) and p=3,q=1(right)

In the next ten years, new energy electric vehicles will usher in a blowout development. Market penetration rises rapidly from low levels to extremely high growth rates. In 2023, the market penetration is expected to be around 40 percent, which is less than half. By 2032, the market penetration of NEEVs is projected to increase significantly to between 75 percent and 85 percent.

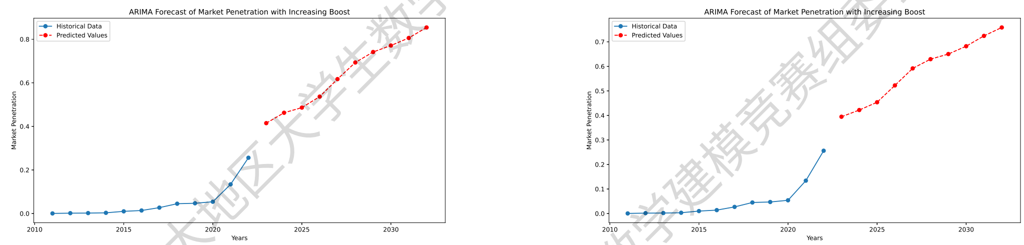


Figure 9 Market penetration rate forecast result of p=3,q=0(left) and p=3,q=1(right)

In the coming decade, New Energy Electric Vehicles (NEEVs) are poised to dominate the automotive industry, capturing nearly 80% of the domestic car market. They will progressively replace conventional fuel vehicles until the market reaches saturation.

VI. An Impact on the Global Traditional Energy Vehicle Industry

6.1 Data Description

6.1.1 *Data collection*

The sales data follows the statistics from problem 1 and 2. The vehicle ownership data is sourced from the International Organization of Motor Vehicle Manufacturers(IOCA) and China News Network.

6.1.2 *Data Pre-processing*

In the quest for reliable modeling, data preprocessing stands as a crucial stage.This process aims to fortify the dataset for modeling purposes.

For global new energy electric vehicles and traditional energy vehicles' sales and ownership data, we chose logistic regression for the former and the least squares method for the latter based on their suitability and goodness of fit calculations. Logistic regression is ideal for categorical outcomes, while the least squares method suits linear relationships, aligning with the nature of the datasets. Moreover, preprocessing the data offers significant benefits, such as improving data quality, refining data fit for models, and enhancing overall analysis robustness.

6.2 Impact Analysis Model: New Energy Electric Vehicles on Traditional Vehicle Market

6.2.1 *Optimal Species Competition Model in Math Modeling*

The optimal choice of the species competition differential equation model in industries hinges on its capacity to replicate intricate interactions among competitors, mimicking the rivalry between new energy electric vehicles and traditional counterparts. This model effectively tracks evolutionary paths and competitive behaviors crucial for assessing emerging technology's impact on established markets. Using vehicle sales and ownership as key metrics is motivated by their ability to portray market penetration and consumer adoption rates comprehensively. Sales figures mirror immediate market acceptance, while ownership signifies long-term commitment and market sustainability, offering a holistic view of the industry's response to the rise of new energy electric vehicles.

⋄ Optimal Species Competition Differential Equation Model for Ownership

The optimal species competition differential equation model represents the dynamic interaction between competing entities in an ecosystem. Mathematically, it is often formulated as:

$$\begin{cases} \frac{dN_1(t)}{dt} = r_1 N_1 (1 - \frac{N_1}{K_1}) - \sigma_1 N_1 N_2 \\ \frac{dN_2(t)}{dt} = r_2 N_2 (1 - \frac{N_2}{K_2}) - \sigma_2 N_1 N_2 \end{cases} \tag{7}$$

$$b = r(1 - \frac{N}{k}) = \frac{d(N(t) - N(t-1))}{dt} \tag{8}$$

We use the subscript 1 to represent the data from the traditional automobile industry, and the subscript 2 to the new energy automobile industry. In this section, N represents the processed data of global holdings; r means the maximum growth rate of the population; K represents maximum population size the environment can sustain; σ means the intensity of competition between entities. b is the average annual growth rate of a certain population when it exists alone.

Based on investigations into industry research reports and official news coverage, we have found that the development of traditional energy has essentially reached saturation in 2022[4] . The growth in ownership is relatively stable, K_2 is infinitely close to the maximum saturation of the market. So the indicators of traditional energy do not conform to the logistic pattern of population change. That leads to the ratio parameter $\frac{N_1}{K_1} = 0$.

According to the definition of each indicator, we associate the existing data with the parameters in the formula: K_2 equals to the ownership of traditional automobile industry in 2022, which is 11,446 million. And the σ here represents the cost performance index. σ_1 is the average electricity cost per 100 kilometers of new energy electric vehicles and the average fuel cost per 100 kilometers of traditional energy vehicles, and σ_2 is the reciprocal of σ_1.

Using the data above, the parameters in the model are determined. Bring these parameters into the model to solve and get the results.

⋄ Optimal Species Competition Differential Equation Model for Sales Volume

The model for sales is roughly the same as the above model, with K_2 changed to 7493.56.

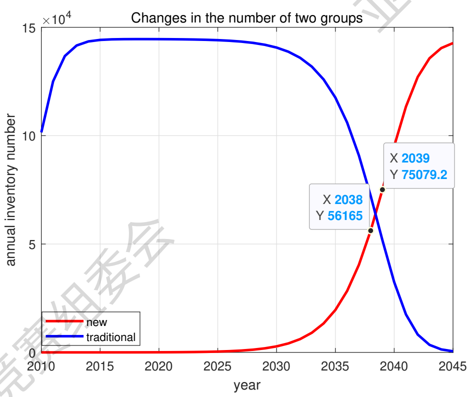
6.2.2 *Results*

Using this model, we obtained competition outcome data. The data of next ten years are showed below as data display, it demonstrates the development of new energy electric vehicles(NEEVs) and traditional energy vehicles(TEVs).

Table 5 Forecast for the development of NEEVs and TEVs in the next ten years

Ownership(000s)		year	Sales Volume(000s)	
NEEVs	TEVs		NEEVs	TEVs
170.064	144356.98	2023	140.142	6600.78
253.653	144237.74	2024	208.285	6504.63
378.289	144059.90	2025	308.972	6363.42
564.081	143794.91	2026	456.989	6157.70
840.929	143400.33	2027	672.851	5861.73
1253.226	142813.37	2028	983.650	5444.14
1866.708	141941.48	2029	1421.927	4872.79
2778.356	140649.12	2030	2019.211	4128.23
4130.402	138739.71	2031	2789.012	3229.47
6129.517	135932.42	2032	3697.395	2263.65

The competition results of the population model for the respective holdings and sales are as follows:



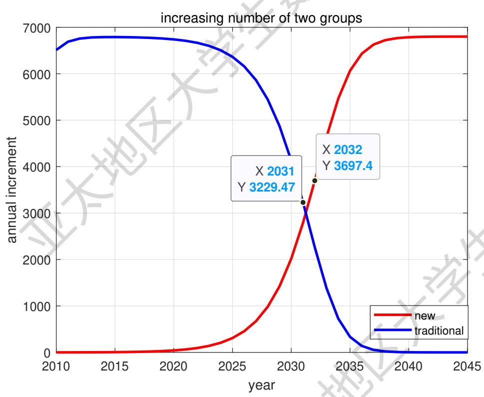


Figure 10 Competition results of ownership(left) and sales(right)

Based on the development trends of the two, the number of new energy electric vehicles and traditional energy vehicles will reach the same level between 2038 and 2039. And in 2041, new energy vehicles will account for more than 86% of the automobile market.

Based on the development trends of the two, the sales of new energy electric vehicles and traditional energy vehicles will reach the same level between 2031 and 2032. And in 2034, new energy vehicles will account for more than 88% of the automobile market.

VII. Resistance to China's NEEVs and the Impact

Because China's share of the new energy electric vehicle market exceeds 50% (data statistics are as of 2022), other countries have introduced policies to protect local companies and inhibit the development of Chinese companies.

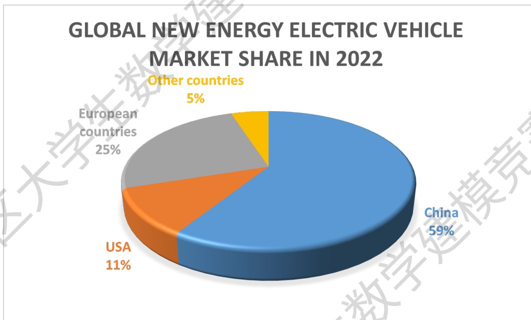


Figure 11 Global new energy electric vehicle market share in 2022

Apart from China, Europe and the United States wield the greatest influence on the market. Hence, we focus solely on evaluating the effects of European and American policies on our country's new energy vehicles.

7.1 Index Setting

Based on a survey of past relevant research papers, China's outbound new energy vehicle exports serve as a direct gauge of foreign policy impact on its electric vehicle industry. These exports reflect market changes due to tariffs, subsidies, and regulations, showcasing how international policies influence demand and industry growth.

Hence, this section selects China's NEEV export volume as the yardstick to assess the influence of foreign policies on the growth of China's NEEV industry. We collect the main policies from October 2021 to October 2023.

- ⋆ **Policy 1 (May 2021):**
  The U.S. Senate Finance Committee passed the "American Clean Energy Act" proposal, which allocates $31.6 billion in electric vehicle consumption tax credits. At the same time, it relaxes the 200,000-unit limit for automakers to enjoy tax credits, excluding Chinese manufacturers.
- ⋆ **Policy 2&3 (February-March 2022):**
  The U.S. House of Representatives passed the American Competition Act, which plans to allocate $52 billion over the next five years to subsidize research and manufacturing in key industries such as semiconductors and automobiles.
- ⋆ **Policy 4 (June 2022):**
  The passage of the tougher "American Innovation and Competition Act" has more powerfully protected the development of domestic companies in the United States.
- ⋆ **Policy 5 (September 2022):**
  The U.S. Inflation Reduction Act has officially become legislation. This bill contains strong unilateralism and protectionist overtones. Only companies that are on the list can enjoy preferential treatment.
- ⋆ **Policy 6 (September 2023):**
  European Commission President von der Leyen announced in her State of the Union address that she would launch a countervailing investigation into China's electric vehicles.

7.2 Difference-in-Differences Model

A difference-in-difference (DID) model is a statistical method used to estimate the causal effects of policy interventions by comparing changes in outcomes over time between experimental and control groups. The model is based on the traditional difference-in-difference (DID) approach, incorporating multiple time periods and/or multiple groups.

The time series settings of policy nodes in our DID model are as follows: when there is a policy, the sequence value takes 1, and when there is no policy, it takes 0. Use the DID model to test the causal relationship between export volume and whether the policy is enacted, and give the correlation (negative correlation)

Judging from the existing monthly export volume data (October 2021 to October 2023), China's export volume of new energy electric vehicles is gradually rising. Therefore, we set the control group data that is not affected by the policy to be the arithmetic sequence distribution from the first group to the last group of existing data, and conduct DID model testing.

7.3 Results

The monthly export volume-policy diagram used in the DID model is as follows:

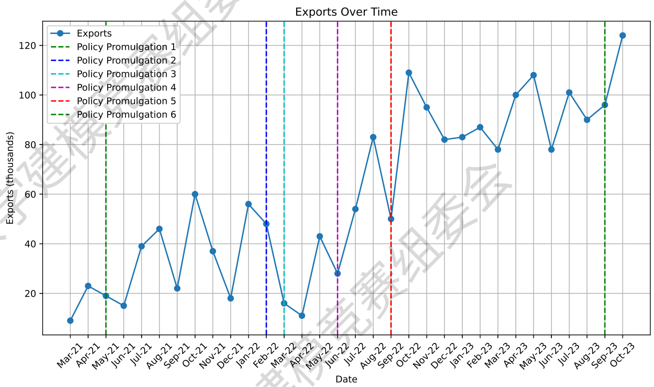


Figure 12 Export volume-policy diagram

And the results of the goodness of fit and policy influence of the DID model we used are as follows:

Table 6 Model Summary

DID model			Policies	
R-squared	**Adj.R-squared**	**Prob (F-statistic)**	**Coef**	**P>|t|**
0.942	0.938	2.72E-19	-15.3499	0.049

The provided DID model exhibits a high goodness of fit, with an R-squared of 0.942 and an adjusted R-squared of 0.938, indicating that approximately 94.2% of the variation in the outcome variable is explained by the included variables. The Prob (F-statistic) of 2.72E-19 is significantly low, suggesting that the model as a whole is statistically significant, indicating that the included variables jointly have a significant effect on the outcome. Additionally, the coefficient of policies is -15.3499, and its associated t-statistic yields a p-value of 0.049, which is marginally below the conventional threshold of 0.05. This indicates a potential significant impact of policies on the outcome variable.

VIII. Making Difference:Changes the Electrification Brings to the City of One Million People

8.1 Data Description

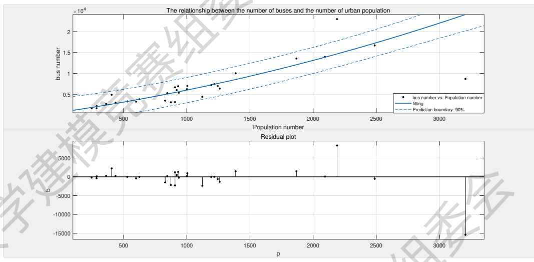
According to authoritative industry reports in the automotive sector and publicly available national information, we have obtained the average electrification rates for buses and cars (M_b,M_c). Additionally, we've acquired the energy consumption equivalents for electric buses and cars (a_1, a_2), where energy consumption equivalents denote the conversion of electricity consumption per hundred kilometers to fuel consumption per hundred kilometers. Furthermore, we have the fuel consumption per hundred kilometers for non-electric buses and cars (b_1, b_2), as well as the carbon dioxide emission coefficient for gasoline (ω).

8.2 Composite Model of Urban Population and Carbon Emissions per Hundred Kilometers

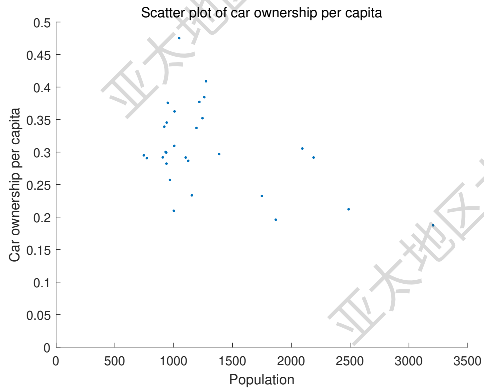
To evaluate the impact of automobile electrification on the ecological environment in a city of one million inhabitants, it requires fitting into two nested models. Given the composition of vehicles in the city, for model simplification, we assume the city's automobiles do not include trucks. We use carbon emissions, the most influential indicator, to assess the impact on the ecological environment. The first step involves analyzing the relationship between urban population and the quantities of electric and non-electric vehicles. The second step involves gathering data to reasonably fit vehicle quantities and carbon emissions, ultimately determining the carbon emissions after electrification for a city of one million inhabitants.

8.2.1 *Urban Population and Fitting Model for Total Public Buses and Cars*

Due to the strong fit between the total number of public buses and the total population (as shown in the figure 13(a)), the estimated total number of buses(L_b) in a city of one million inhabitants is 1161.



(a) **The Graph Fitting Bus Quantity to Urban Population**



(b) **Scatter Plot: Car Ownership per Capita vs. Urban Population**

Figure 13 The Urban Population's Relationship with Total Public Buses and Cars

However, due to the scattered distribution between the total number of cars and the total population (as seen in the scatter figure 13(b)), we perform fitting on the total count. Then, subtracting the bus count from the total count gives us the total number of cars. After fitting, the estimated total vehicles in a city of one million inhabitants are 1.0465 million, from which the number of cars(L_c) can be calculated.

8.2.2 *The Fitted Model for Carbon Emissions and Vehicle Numbers*

We choose the total carbon dioxide emission as the representative indicator for carbon emissions(T) .Establish a model for carbon dioxide concerning the number of urban buses and cars using the following formula:

$$T = \omega \times [(a_1 M_b + b_1(1 - M_b)) L_b + (a_2 M_c + b_2(1 - M_c)) L_c] \tag{9}$$

Finally, we get an estimate of carbon dioxide emissions per 100 kilometers for a city with a population of one million.The calculation result of the model is 21545123.4782328 kilograms.

The figure of fitted model for carbon emissions and vehicle numbers is as follow:

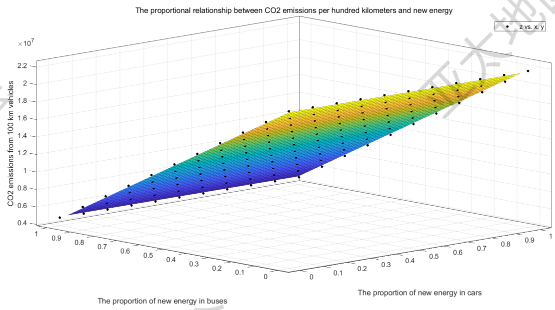


Figure 14 The Fitted Model for Carbon Emissions and Vehicle Numbers

IX. An Open Letter:New Energy Electric Vehicles Moisten Your Life and Mine

Dear Citizens,

As our world navigates through the challenges of environmental sustainability, there's a beacon of hope shining brightly on our roads: new energy electric vehicles. The electrification of transportation, from cars to buses, holds immense promise in transforming our cities into cleaner, healthier, and more sustainable spaces. It's time to recognize how significant these vehicles contribute to protecting our ecological environment.

New energy electric vehicles (NEEVs) are not just a mode of transportation, they represent a pivotal shift toward a greener future. The benefits they offer are multifaceted and impactful. By choosing NEEVs, we collectively contribute to reducing greenhouse gas emissions, curbing air pollution, and mitigating the effects of climate change. We provide the future generations with a quieter, cleaner and safer living environment.

Countries around the world have been embracing the electric vehicle industry in a more positive and open manner. They are adopting proactive measures and policies to drive innovation and foster a revolution in transportation. From the Norway to China, the United States to Netherlands , Governments and industries around the world are increasing investment in NEEV infrastructure and technology. It is precisely because of the accumulated efforts of all parties that the overall improvement in our quality of life has been achieved today.

Electric buses,especially worth to be mention, are silently transforming our cities. They offer They provide a quieter, less bumpy and pollution-free mode of public transportation. Just imagine waiting at a bus stop surrounded by clean air, with buses silently passing by, leaving behind no emissions. It's a vision that's becoming a reality in many cities, thanks to the widespread adoption of electric buses.

The benefits of electric vehicles extend beyond environmental advantages. They also bring economic opportunities, fostering job creation and innovation in clean energy technologies. Moreover, as the NEEV industry grows, the cost of these vehicles continues to decrease, making them increasingly accessible to everyone.

However, this transition requires collective action. Each of us plays a crucial role in accelerating the adoption of electric vehicles. Whether it's choosing an electric car for your daily commute or supporting initiatives that promote NEEV infrastructure, every action contributes to a more sustainable future.

Let's take pride in our collective efforts toward a cleaner and healthier environment. Let's embrace the potential of new energy electric vehicles and support the electric vehicle industry, not just for ourselves but for the well-being of our planet and future generations.

Together, we can drive change, one electric vehicle at a time.

X. Sensitivity Analysis and Error Analysis

When conducting multiple linear regression model in Problem 1, in order to explore the sensitivity of the model,a 85%-115% confidence interval for the most influencing factor should be given.

Observing the value of the regression coefficient β ,we can get the biggest one is belonged to the policy subsidy amount of NEEVs. It confirmed that policy subsidy amount is the most influecing factor. Therefore, we fix the values of other variables and perturb the subsidy coefficient, Obtain a 85%-115% confidence interval for the policy subsidy amount.

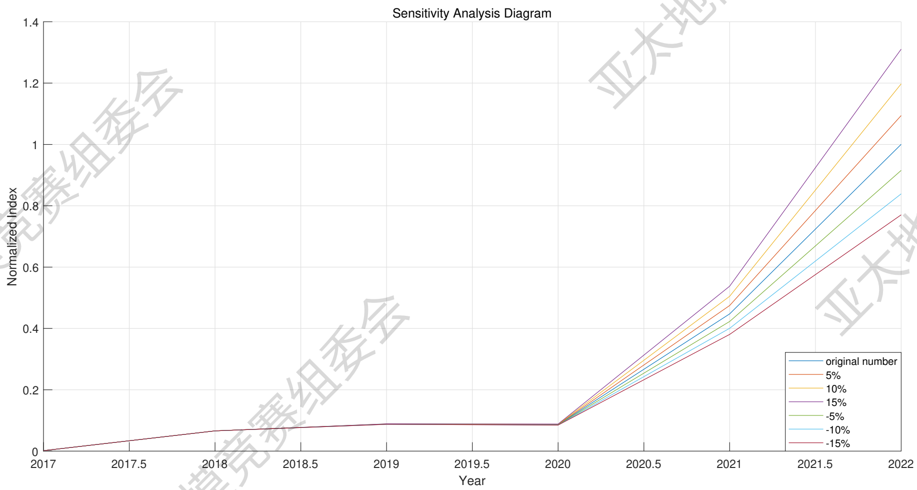


Figure 15 1

The model's conclusion highlights a consistently narrow range of solution fluctuation, indicating a low standard deviation. The accompanying figure illustrates the model's low sensitivity and strong robustness.

XI. Model Evaluation and Further Discussion

11.1 Model Evaluation

11.1.1 *Advantages of the Model*

⋆ In the first question, our strength lies in identifying the factors influencing the development of the new energy industry through relevant research and assessing the extent of their impact, presenting a more intuitive display of their influence.

⋆ Evolving and refining the population competition model to better align with the developmental patterns of industry competition. This model has the capability to forecast the future trends of both new energy vehicle and traditional vehicle industries under their mutual influence, enhancing its scientific validity.

⋆ We utilized a double difference model to analyze the impact of policies on export volume, achieving a good fit. It holds more persuasive strength compared to traditional regression models.

⋆ Building upon the foundation of the environmental impact of automobiles in various Chinese cities, the model constructed is more scientific and representative. It distinguishes between the electrification rates of cars and buses, avoiding a simple aggregate of the two. This approach fully considers the varying degrees of vehicle electrification between cities, rendering the model's outcomes more comprehensive.

11.1.2 *Shortcomings of the Model*

⋆ The collected sample size of data can be expanded further, providing room for additional optimization and improvement of the model.

⋆ In the fifth problem, the discussion focuses solely on two vehicle types: cars and buses, presenting a relatively simplified analysis of vehicle categories.

11.2 Promotion of the Model

⋆ We can collect more indicators and data, and build a more complete and more complex mathematical model for more accurate evaluation of various indicators reflecting the development level of NEEVs.

⋆ We can collect more indicators and data, make a promotion of the Difference-in-Differences Model. Analyze the duration of various policy lags, obtain new policy node time series with policy lags, and establish a more complete DID model, which may lead to better fitting results.

XII. References

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