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Problem Chosen :	C

2023 APMCM summary sheet

Abstract

New energy vehicles (NEVs), a type of vehicle that integrates cutting-edge technology with vehicle power control and drive, have received widespread consumer and government support worldwide. In order to explore the development trend of new energy vehicles more comprehensively, this paper will give an in-depth analysis of the development trend in this field through a detailed analysis of the collected data.

For question 1, by searching for literatures with "new energy vehicles" as the keyword on CNKI, PubMed, Google Scholar and other search websites, we analyzed the frequency of the keywords and selected the index with high frequency as the key index of the research. Finally, we determined 25 indicators in four aspects: economic factors and costs, social macro indicators, market and penetration categories, infrastructure and innovation categories. In order to obtain the data, a variety of approaches were employed, including Python data crawlers and active search. Relevant data were obtained from multiple open databases including the National Bureau of Statistics, the Ministry of Industry and Information Technology, the New Energy Vehicle Association, the World Bank and the Ministry of Public Security. This method helps to fully understand the development of the new energy vehicle sector and provides strong data support.

For data processing, q-q chart and K-S test were used to confirm that the data basically obeyed normal distribution. The outliers are determined and replaced by missing values according to the 3σ principle, and then Newton linear interpolation is used to fill in the missing values. Due to the large number of indicators, KMO test and Bartlett sphericity test were used to evaluate the independence of indicators. The indexes that passed the test were reduced dimensionality by principal component analysis, and the indexes that failed the test were reduced dimensionality by correlation analysis.

For problem 2, the results of data preprocessing in problem 1 were used to forecast by regression prediction, gray prediction, LSTM and other methods, in which ARIMA (autoregressive integral moving average) model was selected. By comparing the performance of different prediction models and taking the minimum error as the objective function, the optimized model is constructed for weighted fusion. The model aims to achieve an accurate prediction of the development trend of new energy electric vehicles in China in the next 10 years. With the goal of minimizing errors, an optimization model has been constructed to provide more reliable forecasts for the future development of the new energy electric vehicle market.

The research of question 3 focuses on establishing an association model between new energy electric vehicles and traditional energy vehicles, and adopts statistics and machine learning methods to comprehensively analyze the dynamic relationship between them. Through the integration of sales volume, market share, technological innovation and other data, to provide a deep understanding of the impact of new energy vehicles on the traditional energy vehicle industry.

As for the fourth question, combined with relevant reports, this paper studies the 27.5% tariff imposed by the United States on Chinese automobiles, and predicts the data before the tariff with the LSTM model. Integrate economic indicators and trade data to predict the future trends of the automobile industry, and provide scientific support for understanding the impact of trade policies on the automobile industry.

For question 5, the city of Tianjin is selected to collect its relevant data from CEADs (China Carbon Accounting Database), and the carbon dioxide emission is used as its ecological environment index. The correlation model was constructed for solving and analyzing. Based on the previous research and data results, write an open letter to citizens to publicize the benefits of new energy electric vehicles around the world.

Key words: association model, data preprocessing, prediction model, optimization model

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一、Problem review

1.1 Question Background

The development trend of new energy electric vehicles in China New energy vehicles refer to the use of unconventional motor fuel as the power source (unconventional motor fuel refers to fuel other than gasoline and diesel), the integration of advanced technology in vehicle power control and drive, with advanced technology, advanced technical principle, new technology, novel structure of the vehicle. New energy vehicles include four major types: hybrid electric vehicles, pure electric vehicles, fuel cell electric vehicles and other new energy vehicles. As a new energy vehicle, new energy electric vehicles (NEVs) have achieved rapid development in recent years due to their characteristics of low pollution, low energy consumption and peak power regulation. New-energy electric vehicles, including electric buses and household electric vehicles with fewer than seven seats, have been popular with consumers and governments around the world.

Since 2011, the Chinese government has actively promoted the development of new energy electric vehicles and formulated a series of preferential policies. The new-energy electric vehicle industry has achieved great development, gradually becoming another symbol of China after "China's high-speed rail". Now, ask your team to complete the following questions."

1.2 Problem Analysis

Question 1: Analyze the main factors affecting the development of new energy electric vehicles in China, establish a mathematical model, and describe the impact of these factors on the development of new energy electric vehicles in China.

Question 2: Collect the industry development data of China's new energy electric vehicles, and establish a mathematical model to describe and predict the development of China's new energy electric vehicles in the next 10 years.

Question 3: Collect data and establish a mathematical model to analyze the impact of new energy electric vehicles on the global traditional energy vehicle industry.

Question 4: Some countries have formulated a series of targeted policies to resist the development of new energy electric vehicles in China. A mathematical model is established to analyze the impact of these policies on the development of new energy electric vehicles in China.

Question 5: Analyze the impact of electrification of urban new energy electric vehicles (including electric buses) on the ecological environment. Assume that there are 1 million urban population and provide the calculation results of the model.

Question 6: Based on the conclusions of question 5, write an open letter to the public to publicize the benefits of new energy electric vehicles and the contribution of the electric vehicle industry in various countries around the world

二、Problem analysis

2.1 Problem 1 Analysis and data preprocessing

For question 1, by searching the literature with the keyword "new energy vehicle" on CNKI, PubMed, Google Scholar and other search websites, we analyzed the frequency of the keywords and selected the index with high frequency as the key index of the research. Finally, we determined 25 indicators in four aspects: economic factors and costs, social macro indicators, market and penetration categories, infrastructure and innovation categories. In order to obtain the data, a variety of approaches were employed, including Python data crawlers and active search. Relevant data were obtained from multiple open databases including the National Bureau of Statistics, the Ministry of Industry and Information Technology, the New Energy Vehicle Association, the World Bank and the Ministry of Public Security.

For data processing, q-q chart and K-S test were used to confirm that the data basically obeyed normal distribution. The outliers are determined and replaced by missing values according to the 3σ principle, and then Newton linear interpolation is used to fill in the missing values. Due to the large number of indicators, KMO test and Bartlett sphericity test were used to evaluate the independence of indicators. The indexes that passed the test were reduced dimensionality by principal component analysis, and the indexes that failed the test were reduced dimensionality by correlation analysis.

2.2 Analysis of Problem 2

Based on the data preprocessing results of question 1, we adopt regression prediction, gray prediction, LSTM and other methods, in which ARIMA model is used. Finally, an optimization model is constructed with the minimum error as the objective function, which can accurately predict the development trend of China's new energy electric vehicles in the next 10 years. This comprehensive model provides a more reliable forecast for the future development of the new energy electric vehicle market by weighted fusion of the results of multiple prediction models.

2.3 Analysis of Problem Three

The research of question 3 focuses on establishing the correlation model between new energy electric vehicles and traditional energy vehicles, and adopts statistics and machine learning methods to conduct comprehensive analysis. Integrate sales volume, market share, technological innovation and other data to deeply understand the impact of new energy vehicles on the traditional energy vehicle industry.

2.4 Analysis of Problem 4

The study in question 4 focuses on the scenario in which the United States imposes a 27.5% tariff on Chinese-made cars, which has been in effect since November 2018. By combining relevant reports, we will use the LSTM model to forecast the data before November 2018, and compare the predicted results with the actual values to deeply explore the impact of this tariff policy on the automobile industry.

2.5 Problem Five or Six analysis

For question 5, the city of Tianjin is selected to collect its relevant indicators, and the carbon dioxide emission is used as its ecological environment indicator. The correlation model is constructed for solving and analyzing. Based on the previous research and data results, write an open letter to citizens to publicize the benefits of new energy electric vehicles around the world.

三、Model assumption

We will adopt the following assumptions to better model:

1. Environmental Impact Assessment: We assume that environmental impact assessment can be carried out by measuring the relationship between the ownership and sales of new energy vehicles and carbon emissions. This is based on the view that the promotion and popularization of new energy vehicles will have a positive impact on overall carbon emissions.

2. Impact of policy changes: We assume that policy changes, especially tariff changes, have a significant impact on the NEV market and may cause sales volume fluctuations. This takes into account the direct impact of policy factors on the automotive industry, and tariff changes may lead to market changes.

3. Positive impact of urban electrification on the ecological environment: We assume that electrification of urban new energy electric vehicles has a positive impact on the ecological environment and can effectively reduce total carbon emissions. This reflects the positive impact of the environmental protection nature of electric vehicles on the environment.

4. Environmental Impact Assessment focuses on carbon emissions: We will focus on carbon emissions as the primary and most direct indicator for assessing environmental impact. This selection reflects carbon emissions as the core factor in measuring environmental friendliness.

5. Unrecorded external factors ignored: We assume that the impact of any external factors not explicitly recorded in the data set (such as macroeconomic conditions, policy changes, etc.) on the forecast results is ignored. This simplification helps to keep the model relatively concise, focusing on the effects of the main factors.

These assumptions provide the basis for building a predictive model, but in actual analysis, the model results need to be closely monitored and possible external factors considered to ensure the accuracy and usefulness of the model.

四、Symbol Description

To facilitate the model building and solving process, here are the key symbols used:

Symbols	Instructions
Δy_t	First difference for y_t
p	The weight obtained by the entropy weight method
$f[x_0, x_1, ..., x_n]$	Order of lag
x_i	i th missing item
n	Number of missing items
S_x	Sample standard deviation
r_{xy}	Sample Pearson correlation coefficient
y_t, y_{t-1}	Is the value of the variable at time t and time t-1
ε_x	White noise sequence
$y_{真实}$	Real data
$forecast(t)$	Predicted value
$actual(t)$	Real value
$Cov(x, y)$	Sample covariance

五、Building and solving the model

5.1 Establishment and solution of problem 1 model

5.1.1 Identification of factors

The development of new energy electric vehicles in China is influenced by a combination of multiple factors, which are intertwined and interact with each other to shape this dynamic market. Specifically, the key factors include:

1. Policy factors: Emission restrictions and subsidy policies set by the government directly affect the NEV market. The continuity and stability of policies is crucial to the development of the industry, which can provide direction to enterprises and stimulate investment enthusiasm.

2. Technological factors: The new-energy electric vehicle market has always been at the forefront of technological innovation. Continuous breakthroughs in battery technology, charging technology and intelligent driving have not only improved vehicle performance, but also expanded consumers' expectations for new energy vehicles.

3. Resource and environmental factors: Improved charging infrastructure and society's increasing emphasis on environmental protection have a direct impact on the market penetration rate of new energy vehicles. The acceleration of urbanization has also provided a broader space for development of new energy vehicles. Economic factors: fuel price, electric vehicle charging cost, average vehicle price and so on will affect consumers to buy new energy electric vehicles.

4. Economic considerations: Consumers' economic sensitivity to fuel prices, EV charging costs, and vehicle prices are key factors influencing their car purchase decisions. Price rationality is directly related to the popularity of the market.

5. Market factors: consumers' demand for and acceptance of new energy directly shape the market demand for new energy electric vehicles. The diversified demand of the market is also reflected in the continuous innovation of models and functions.

6. Social factors: Society's demand for low energy consumption and low emission vehicles will affect the development of new energy electric electric vehicles.

In the process of consulting relevant literature and materials, through the use of CNKI, PubMed, Google Scholar and other periodical search websites, the keyword is "new energy vehicles", and finally collected 24 relevant literature. The keywords involved in these literatures were marked with frequency, and the indicators with high frequency were selected as important indicators for the study of the development of new energy vehicles. This comprehensive research method more comprehensively reveals the development trend of China's new energy electric vehicle market, and provides strong support for further in-depth analysis. The related indicators are shown in the following diagram:

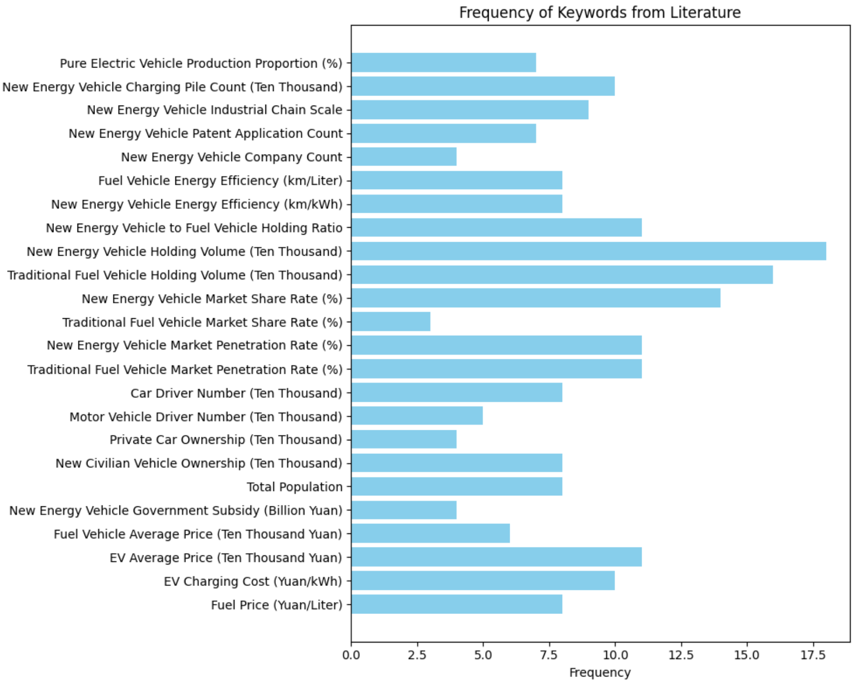


Figure 1: Indicator frequency

5.1.2 Determination of indicators

The following are the indicators of the development of new energy vehicles in China:

Table 1: Development indicators of new energy electric vehicles in China

First-level indicators	Secondary indicators	Tertiary indicators
Factors affecting the development of new	Policy-related Indicators	Emission standards for new energy vehicles
		Government subsidies

energy vehicles	Technology-related indicators	China's new energy vehicle patent applications
		Number of registered power battery enterprises
		Number of registered battery recycling enterprises
		Smart driving and connectivity technologies
		Total amount of investment and financing disclosed in the new energy vehicle industry
	Economy-related indicators	GDP per capita
		Selling price, maintenance cost, charging cost
		Oil reserves and oil fuel prices
	Resources and environment related indicators	Number of public charging piles
		The impact of oil price fluctuations on car purchase decisions
		The impact of new energy vehicles on environmental carbon emissions
	Social benefit related indicators	The cognition level of new energy vehicles
		Gross enrollment rate of higher education
		Number of drivers
	Market development indicators	Sales volume and market share of new energy vehicles
		Consumer demand for and acceptance of new energy vehicles
		The integrity and stability of the new energy vehicle industry chain

These five categories of indicators provide comprehensive data support for the mathematical model, and in-depth analysis of the development of China's new energy electric vehicles from different perspectives. The comprehensive analysis of these indicators helps to understand how factors inside and outside the industry work together to influence the development of NEVs. When implementing the model, these classifications are able to clearly organize the data, assess the influence of each category separately, and may reveal the interaction between these factors.

This comprehensive analysis method enables a more comprehensive grasp of the dynamics of the NEV market and provides more accurate information support for decision makers. By comprehensively considering the indicators of policy, technology, resources, environment, economy and society, we can better understand the current situation and future trend of the new energy vehicle industry. This in-depth analysis provides a powerful reference for formulating future development strategies, making the decision-making process more scientific and reliable.

5.1.3 Data pre-processing

5.1.3.1 Outliers

The Kolmogorov-Smirnov test is a non-parametric statistical test that is used to test whether a data set follows a certain distribution, the most commonly used of which is to test whether a data set follows a normal distribution. The basic principle is to compare the cumulative distribution function of the data set with the theoretical distribution function, and determine whether the data set conforms to that theoretical distribution by calculating the maximum gap between the two. If the maximum gap is less than a certain critical value, the data set is considered to conform to the theoretical distribution, and the one-sample K-S test is used to test whether the observational empirical distribution of a data is a known theoretical distribution. When the gap between the two is small, the sample is inferred from the known theoretical distribution. The theoretical distribution that serves as the null hypothesis is generally a one-dimensional continuous distribution F(e.g., normal distribution, uniform distribution, exponential distribution, etc.), and is sometimes used for discrete distributions (e.g., Poisson distribution). [1] [1]I.e. H: Population X follows some one-dimensional continuous distribution F. The test statistic is

$$Z = \sqrt{n}\max_i(|F_n(x_{i-1}) - F(x_i)|, |F_n(x_i) - F(x_i)|)$$

H true and Z converges to the Kolmogorov-Smirnov distribution. That is, when the sample is taken from the one-dimensional continuous distribution F:

Note: When F is a continuous distribution, the distribution of the random variable K does not depend on F.

The results of the KS test are usually measured by the p-value, and if the P-value is less than the preset significance level (generally 0.05), then we have enough evidence to reject the null hypothesis that the observed data is significantly different from the theoretical distribution and that the two samples come from different distributions. The choice of this significance level usually depends on the specific context and needs of the study, and in general, 0.05 is a common selection criterion.

We need to use SPSS to perform Q-Q plotting and Kolmogorov-Smirnov test for part of the data. The analysis results of Kolmogorov-Smirnov test are as follows:

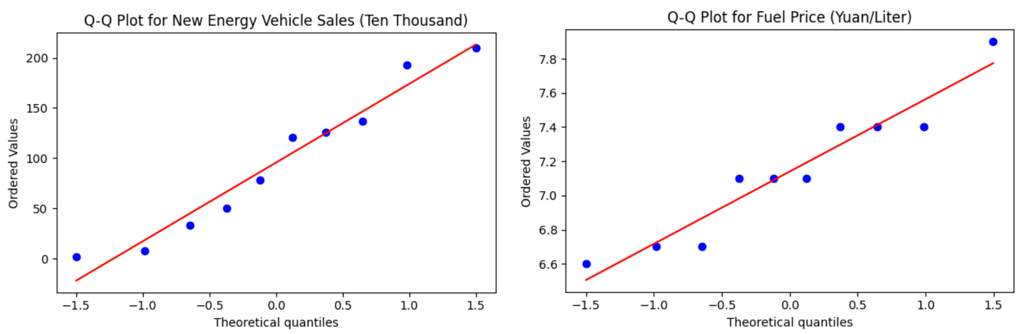


Figure 2: q-q chart

Fuel Price(Yuan / Liter)	0.74872
EV Charging Cost (Yuan/kWh)	0.99619
EV Average Price (Ten Thousand Yuan)	0.99892
Fuel Vehicle Average Price (Ten Thousand Yuan)	0.99967
New Energy Vehicle Government Subsidy (Billion Yuan)	0.99795
Total Population	0.79108
New Civilian Vehicle Ownership (Ten Thousand)	0.98005
Private Car Ownership (Ten Thousand)	0.99843
Motor Vehicle Driver Number (Ten Thousand)	0.95826
Car Driver Number (Ten Thousand)	0.98226
Traditional Fuel Vehicle Market Penetration Rate (%)	0.98403
New Energy Vehicle Market Penetration Rate (%)	0.88039
Traditional Fuel Vehicle Market Share Rate (%)	0.88337
New Energy Vehicle Market Share Rate (%)	0.88337
Traditional Fuel Vehicle Holding Volume (Ten Thousand)	0.9873
New Energy Vehicle Holding Volume (Ten Thousand)	0.83458
New Energy Vehicle to Fuel Vehicle Holding Ratio	0.95292
New Energy Vehicle Energy Efficiency (km/kWh)	0.99967
Fuel Vehicle Energy Efficiency (km/Liter)	0.99967
New Energy Vehicle Company Count	0.98643
New Energy Vehicle Patent Application Count	0.72589
New Energy Vehicle Industrial Chain Scale	0.9994
New Energy Vehicle Charging Pile Count (Ten Thousand)	0.76802
Pure Electric Vehicle Production Proportion (%)	0.66434

Table 2: K-S examines full data

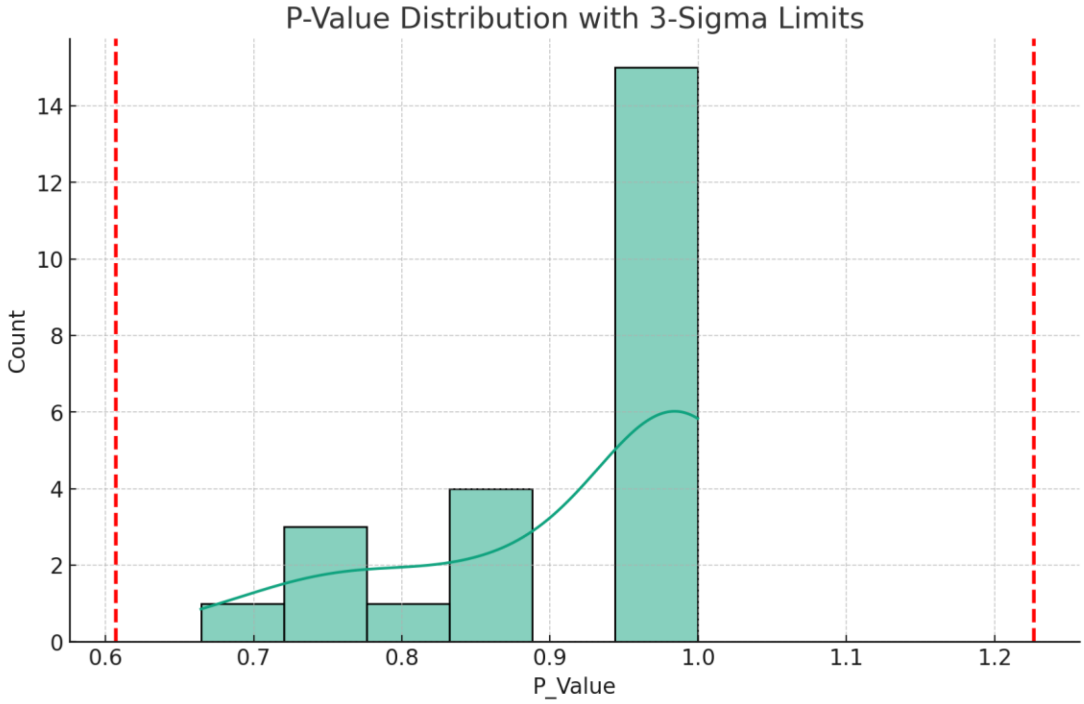
Through analysis, we find that most of the data are normally distributed, so we introduce the 3σ principle. This rule determines outliers, taking into account the properties of a normal distribution. According to the 3σ principle, 99.7% of the data is within three standard deviations of the mean. When a data point falls outside of three standard deviations, the probability is less than 0.3% and it is considered an outlier.

The 3 formula for determining an outlier is as follows:σ

$$P(\ |x-\mu|\ > 3\sigma\ )\ \le\ 0.003$$

Where, is a data point in the data set, is the mean of all the data under that metric, and σ is the standard deviation of all the data under that metric. μ μ

Finally, by artificial judgment and combining the actual situation, we find that there is an outlier in the market penetration of conventional fuel vehicles in a given dataset in 2019. In response to this outlier, we decided to replace it with a missing value and adjust accordingly in the next step of processing.



Year	Traditional fuel vehicle market penetration (%)
2013	99.9
2014	99.6
2015	98.7
2016	98.2
2017	97.4
2018	96.4
2019	85.2 (Abnormal data)
2020	94.3
2021	93.6
2022	92.7

5.1.3.2 Missing values

For a given data, use the find function in MATLAB to find missing values. It is found that there are some missing values in some data, which mainly comes from two aspects, one is the missing introduced by outlier processing, and the other is the missing of data collection itself. For these two cases, we use the way of interpolation filling to deal with.

Year	**Traditional fuel vehicle market penetration (%)**	**Energy efficiency of new energy vehicles (km/KWH)**
2019	-	6
2020	94.3	6.3
2021	93.6	-
2022	92.7	6.9

For this kind of missing value, if it is no longer used directly, it will certainly have some impact on the result. Therefore, the method of interpolation filling is used here for processing. For the missing data contains several nodes with abnormal missing values, which is exactly the data we need to study the following problems, so we use Newton interpolation to supplement this part of missing values. [2]

$$\varepsilon_n(x) = f(x_0) + (x - x_0) f(x_0, x_1) + (x - x_0)(x - x_1) f[x_0, x_1, x_2] + \ldots$$
$$+(x - x_0)(x - x_1)\ldots(x - x_n) f[x_0, x_1, x_2, \ldots, x_n]$$
$$\text{其中，} f[x_0, x_1, x_2, \ldots, x_n]\text{为差商}$$
$$f[x_0, x_1, x_2, \ldots, x_n] = \frac{f[x_0, x_1, x_2, \ldots, x_{n-1}] - f[x_0, x_1, x_2, \ldots, x_n]}{\mathrm{x}\text{-}x_n}$$

Where n is the number of missing items, representing the i th missing item. x_i We use this formula to import the data into MATLAB for calculation, and get some results as follows:

Year	Market penetration of conventional fuel vehicles (%)	Energy efficiency of new energy vehicles (km/KWH)
2019	95.3	6
2020	94.3	6.3
2021	93.6	6.6
2022	92.7	6.9

5.1.3.3 Dimensionality reduction

Firstly, KMO test and Bartlett sphericity test were carried out to evaluate the correlation between the secondary indexes under the primary indexes, so as to provide a basis for selecting the dimensionality reduction method. The principal component analysis method is mainly used for dimensionality reduction of multidimensional indicators, because in the principal component analysis, the greater the correlation between indicators, the better the dimensionality reduction effect.

KMO test and Bartlett sphericity test are used to determine collinearity or correlation between indicators. For the indexes that fail these two tests, we use t-SNE method to reduce the dimensionality of the multidimensional nonlinear indexes to a two-dimensional sequence to achieve the purpose of dimensionality reduction. Such analysis helps to better understand the relationship between indicators, and provides a basis for the subsequent study of dimensionality reduction selection.

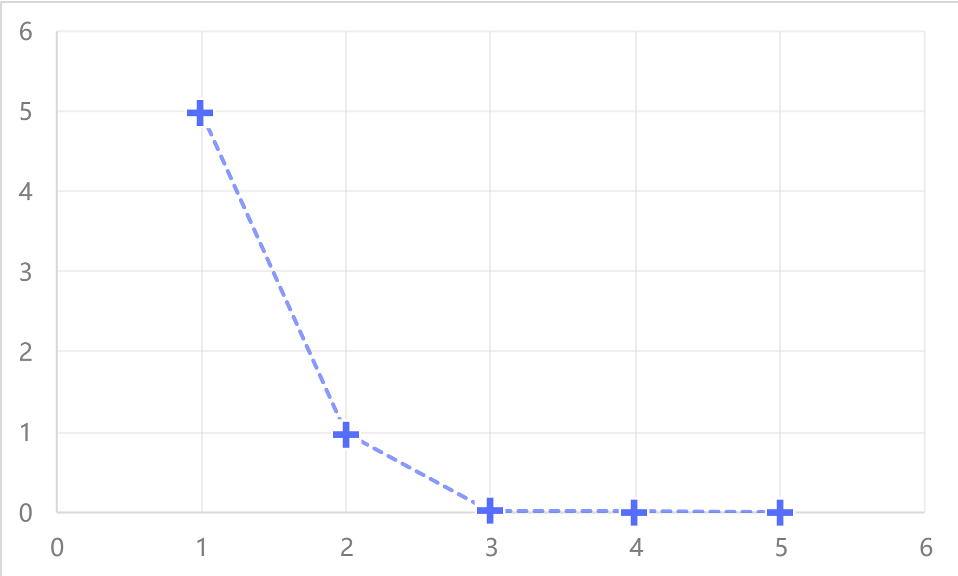
Table 10: Results of KMO test and Bartlett sphericity test

Index Group	KMO values	Bartlett sphericity test (Chi-square value, df, p-value)
Economic factors and costs	0.75	113.293 (10, p < 0.001)
Social macro indicators	0.644	103.379 (10, p < 0.001)
Market and penetration class	0.811	329.189 (21, p < 0.001)
Infrastructure and Innovation	0	0(21,NaN)
New category	0	0(21,NaN)

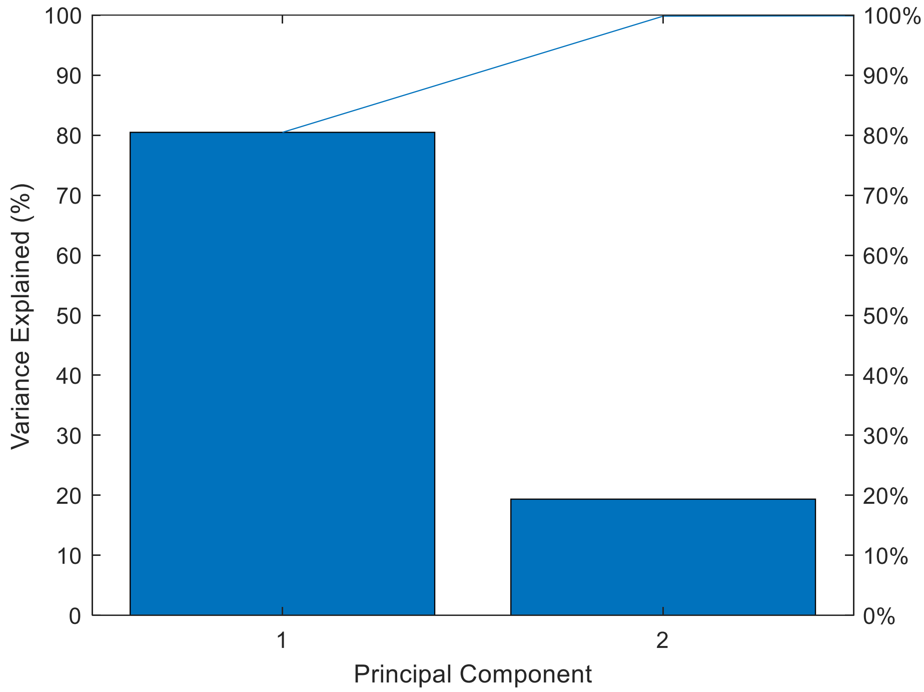
Principal component analysis main steps for dimensionality reduction:

1. **Data standardization:** The raw data is standardized to ensure that each variable has a similar scale to avoid inaccurate results due to differences in variable units.
2. **Calculate the covariance matrix:** Calculate the covariance matrix for the normalized data. The covariance matrix reflects the linear relationship between the variables.
3. **Calculate eigenvalues and eigenvectors:** Perform eigenvalue decomposition on the covariance matrix to obtain the eigenvalues and corresponding eigenvectors. The eigenvalues represent the magnitude of the explanatory variance for each principal component, and the eigenvectors represent the direction of the principal component.
4. **Select Principal components:** Select the number of principal components to keep based on the size of the eigenvalues. Usually, the number of principal components to retain can be determined by the cumulative contribution rate of the eigenvalues so that the cumulative contribution rate reaches a set threshold.
5. **Build a projection matrix:** Build a projection matrix from the eigenvectors of the selected principal components, which is used to project the original data into the principal component space.
6. **Data projection:** Use the projection matrix to project the original data onto the selected principal component to get the data after dimensionality reduction.
7. **Interpret the results:** Interpret and analyze the data after dimensionality reduction. By looking at the weights (loads) of each principal component, it is possible to understand the characteristics that each principal component represents.
8. **Visualization: Visualization** of the data after dimensionality reduction, usually using a scatter plot or other visualization tool to show the distribution of the data in the principal component space.

In order to display the results more intuitively, a lithotripsy diagram is drawn for visual expression:



Through the combination of charts and graphs, we select the principal components, and choose the first two principal components as the new indicators. In order to increase the explainability of the new index, the variance visualization of the cumulative interpretation is drawn by matlab. It is shown below:



Through principal component analysis, the index of economic factor and cost is reduced in dimension, and the results are as follows:

Year	Sales of new energy vehicles (10,000 units)	Economic factors and costs
2013	1.76	1.344
2014	7.48	1.258

2015	33.11	0.636
2016	50.7	0.075
2017	77.7	0.161
2018	125.6	0.161
2019	120.6	0.22
2020	136.6	0.876
2021	192.8	0.875
2022	210.1	0.869

For the infrastructure and innovation class that fails to pass the test, correlation analysis can be introduced. Here, a correlation analysis model can be established and person correlation can be introduced. To judge the relationship between indicators. Sample covariance:

$$Cov\left(x,y\right)=\frac{\sum_{i=1}^{n}(X_I-X)(Y_i-Y)}{n-1}$$

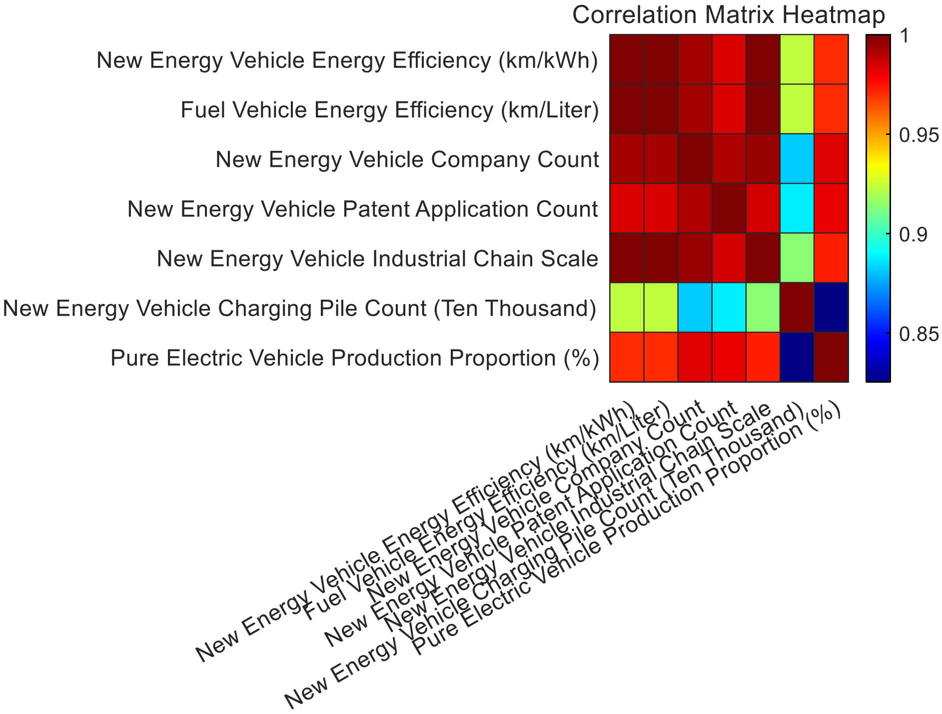
Sample standard deviation:

$$S_x=\sqrt{\frac{\sum_{i=1}^{n}(X_i-X)^2}{n-1}}$$

Sample Pearson correlation coefficient:

$$r_{xy}=\frac{Cov\left(x,y\right)}{S_xS_y}$$

To increase the visualization of the results, a matrix heat map of the correlation analysis was plotted using matlab, as follows:



According to the correlation analysis results, we can draw the following conclusions:

The indicators are highly correlated, the correlation coefficient is close to 1, and the statistical significance is extremely high (the P-value is close to 0, and the significance level of 0.1% is labeled *). In particular, the correlation between "fuel vehicle energy efficiency" and "new energy automobile industry chain scale", "number of new energy automobile enterprises" and "number of new energy automobile patent applications" is close to 1, indicating that there may be a strong positive correlation.

The correlation is low, especially the correlation coefficient between the "number of new energy vehicle charging piles" and other indicators, especially the "number of new energy vehicle enterprises" and "number of new energy vehicle patent applications" is lower than 0.9, but it is still significant.

Significance markers, all of the correlation coefficients are significant at the significance level of 1%, which indicates that these findings are very reliable.

Therefore, for the infrastructure and innovation category, we directly use fuel vehicle energy efficiency (km/L) as the fourth category indicator, instead of the other indicators. Finally, the dimensionality reduction results are summarized, and the results are shown in the following table:

Year	Sales of new energy vehicles (10,000 units)	Economic factors and costs	Social macro Indicators	Market and penetration classes	Infrastructure and Innovation
2013	1.76	1.344	1.603	1.118	4.2
2014	7.48	1.258	1.119	1.012	4.5
2015	33.11	0.636	0.72	0.792	4.8

2016	50.7	0.075	0.008	0.601	5.1
2017	77.7	0.161	0.283	0.329	5.4
2018	125.6	0.161	0.441	0.011	5.7
2019	120.6	0.22	0.539	0.343	6
2020	136.6	0.876	0.531	1.073	6.3
2021	192.8	0.875	0.932	0.934	6.6
2022	210.1	0.869	0.709	1.515	6.9

5.1.4 Establishment of multiple linear regression model:

Multiple linear regression analysis is a statistical method used to evaluate the relationship between a dependent variable and multiple independent variables. The basic idea is to reveal the linear dependency between several independent variables and one dependent variable in a population through a mathematical model. Here, the independent variable refers to the variable that can change independently, while the dependent variable is the variable that is affected by other variables rather than independent.

When analyzing the main factors for the development of new energy electric vehicles in China, it is necessary to take into account many aspects such as policy, resource environment, market, economy, social benefits and technology. These factors constitute a complex system, and each factor influences and restricts each other. In order to more accurately describe the impact of these factors on the development of new energy electric vehicles in China, a multiple linear regression model can be built.

This model will take into account multiple independent variables, each representing an influencing factor, while the dependent variable represents the development status of NEVs. By analyzing the weights of each independent variable, the degree of influence of different factors on the new energy vehicle industry can be revealed, thus helping to formulate a more effective development strategy.

Through multiple linear regression analysis, we can deeply understand the relationship between various factors, and provide data support for the formulation of comprehensive and scientific policies and strategies. This approach contributes to a more systematic understanding of the new energy electric vehicle market and provides more targeted recommendations for future development directions.

Assume that the development level of China's new energy electric vehicles is Y, and the factors such as policy, resources and environment, market, economy, social benefits and technology are X1,X2,X3,X4,X5 and X6, respectively. Then the multiple linear regression model can be expressed as:

Y = 0 + beta beta X1 X2 + + beta 2 * 1 * beta * 3 X3 X4 + beta 5 + beta 4 * * x 5 + beta * 6 X6 + Ɛ

Whereβ0, is the constant term, 1, 23, 4 and 5 are the regression coefficients of each factor respectively, and ββ、βββƐ is the random error term. This is a simple linear model. In fact, more complex models may be more accurate due to possible interactions and nonlinearities among the factors.

Through a large number of collected data, Matlab is used here for multiple linear regression analysis, and the relationship between the development level of China's new energy electric vehicles and various factors is as follows:

Y =212.9545 +1.2760*X1-0.4726*X2-3.7554*X3-4.1605*X4+2.7957*X5+0.5023*X6

Draw residuals to draw residuals and their confidence Spaces to evaluate the fit of regression models:

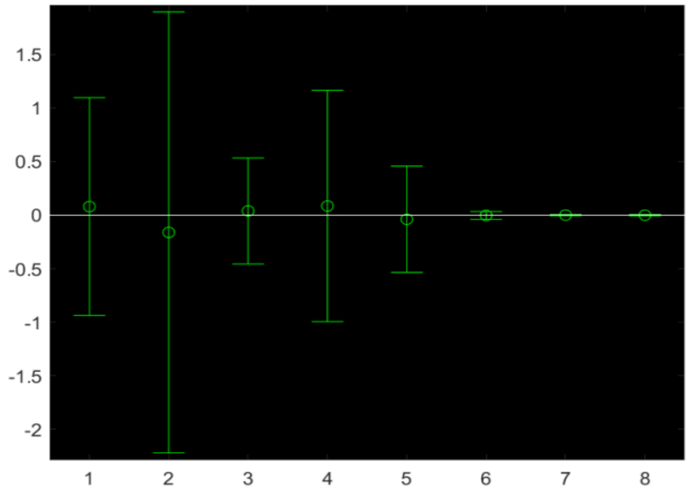


Figure 1: Residuals case order diagram

From the graph, it can be observed that all data points are distributed above and below the 0 axis, which indicates that the difference between the predicted and true values is relatively small, showing a good fit of the model. Next, we will further evaluate the main factors of these several factors through the stepwise regression method of multiple linear regression and select the best model. First, we will get a graph of the coefficients with error bars to give a clearer picture of the influence of each factor on the model. With stepwise regression, we can step by step select the independent variables that have the most significant influence on the dependent variables, resulting in a more refined and accurate model.

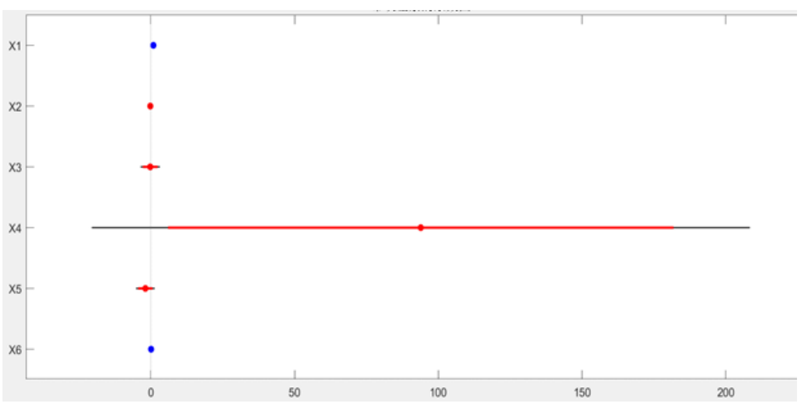


Figure 2: Stepwise Plot

By constantly adding and removing variables, it is finally concluded that when only X1 (policy factor) and X6 (technical factor) are added, R-square is closest to 1, p-val is closest to 0, and the model is more significant. So linear regression is done for the variables Y and X1, X6. The multiple linear regression model is then expressed as:

$$Y = \beta 0 + \beta 1X1 + \beta 6X6$$

Beta 0=-9.1341, beta 1=0.9238, beta 6=0.1307

That is Y=-9.1341+0.9238X1+0.1307X6

To draw a 3D graph:

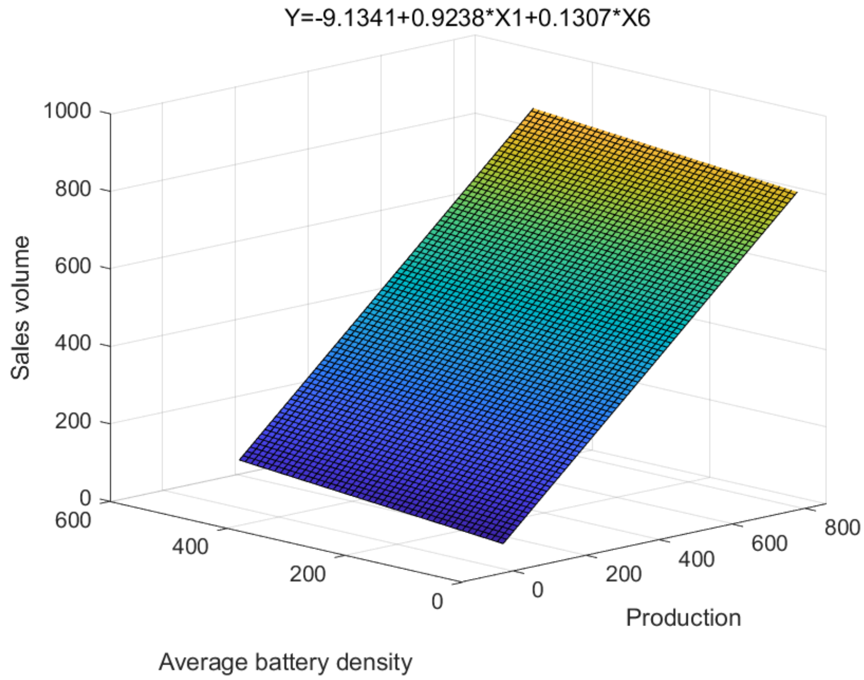


Figure 3: Drawing a 3D graph based on the regression equation

Through the research results of the multiple regression model, we conclude that policy factors and technical factors have the most significant correlation in the development of new energy electric vehicles in China, and can be identified as the most important influencing factors. Therefore, we suggest that in the process of promoting the development of new energy electric vehicles, the top priority is to strengthen policy support. By formulating more active policies, the greater the government's support, the more rapid the development of new energy electric vehicles will be.

Second, we have also stressed the importance of promoting technological development. In this regard, there is a particular need to increase investment in research and development of key technologies such as electric motors and batteries. In addition, it is also crucial to upgrade the level of high-voltage safety technology, which helps improve the performance and safety of new energy electric vehicles. Through the promotion of technological innovation, we can effectively promote the comprehensive development of new energy electric vehicles.

Therefore, in general, we propose to make joint efforts in both policy and technology to promote the sustainable development of NEVs in China. The positive guidance of policies and continuous innovation in technology will jointly push new energy electric vehicles towards a higher level of performance and more reliable safety, thus laying a solid foundation for the vigorous development of the entire industry. 5.2 Establishment and solution of Problem 2 model

5.2.1 Model analysis

The ARIMA (autoregressive Integrated Moving Average) model is a commonly used method for time series analysis and forecasting. The basic idea is to treat time series data as a random series and then use a mathematical model to fit this series to make predictions of future values. There are four basic forms of ARIMA models, namely the autoregressive model (AR model), the moving average model (MA model), the autoregressive moving average hybrid model (ARMA model) and the differential integrated moving average autoregressive model (ARIMA model).

- **AR models (autoregressive models) :** Use observations at past points in time to predict future values. The model parameter is the number of autoregressive terms (p).
- **MA model (moving average model) :** Using a linear combination of past white noise errors to predict future values. The model parameter is the number of moving average terms (q).
- **ARMA model (autoregressive moving average Hybrid model) :** combines AR and MA models with two parameters, the number of autoregressive terms (p) and the number of moving average terms (q).
- **ARIMA model (Differential Integrated moving average autoregressive model) :** The difference term is introduced on the basis of the ARMA model for dealing with non-stationary time series. The model parameters are the number of autoregressive terms (p), the number of differences (d) and the number of moving average terms (q).

The parameters p, d and q of ARIMA model represent the order of autoregression, difference order and moving average order respectively. The selection of these parameters usually needs to be determined by observation and statistical testing of the time series data. The advantage of ARIMA model is that it can adapt to a variety of different time series models, providing a more flexible modeling method.

Here, take the sales volume of new energy vehicles in China as an example to make ARIMA model prediction:

（1）Obtain raw time series data:

The original time series data of China's new energy vehicle sales (10,000 units) is shown in Figure 4. Autocorrelation graph and bias
Autocorrelates are shown in Figure 5, Figure 6.

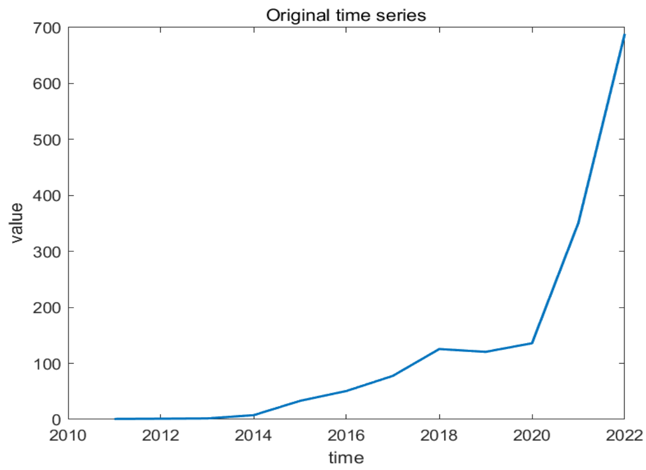


Figure 4: Raw time series data of China's new energy vehicle sales (10,000 units)

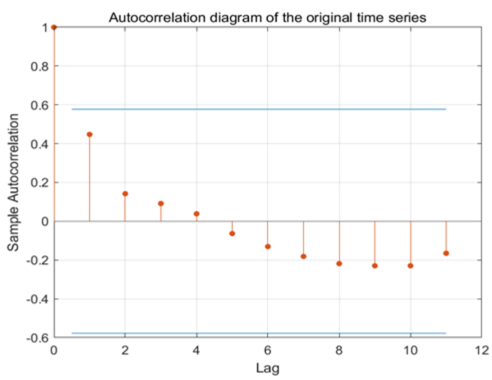
(2) In order to determine the d value in the ARIMA model, it is necessary to first ensure that the time series is smooth. Stationarity tests usually involve the following steps:

1. **Looking at the original series graph:** Chart the original time series to see if there is a trend or seasonality.
2. **Autocorrelates and partial autocorrelates:** Draw autocorrelates and partial autocorrelates of the original series and initially determine whether differences are needed by observing the decay of the graphs.
3. **Unit root test:** Use unit root test (such as ADF test) to determine whether the sequence is stationary. If the original sequence is not stationary, a difference is required.

The original time series of China's new energy vehicle sales are analyzed by autocorrelation graph and partial autocorrelation graph. According to the analysis results, it is necessary to judge whether the series has a trend or seasonality, and carry out a unit root test. If the sequence is not stationary, a difference is required.

In this case, the degree (d value) of the difference is determined by seeing if the sequence becomes stationary after the difference. If the sequence is stationary after the first difference, it is called a single integral sequence of the first order, and an ARIMA model can be built for this sequence after the difference.

To sum up, the d value in the ARIMA model can be determined through the above steps to ensure that the time series is stationary before modeling.



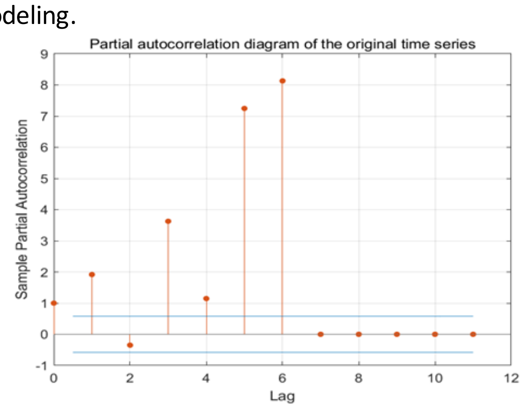


Figure 5: Autocorrelation diagram Figure 6: partial autocorrelation diagram

As can be seen from the graph, the data is not stationary, so we make a difference, that is, d=1.

(3) Determination of p and q values of ARIMA model

Information criteria such as AIC (Akaike Information Criteria) and BIC (Bayesian Information criteria) are often used. By trying different combinations of p and q, calculate the corresponding AIC and BIC values, and then choose the combination with the minimum AIC and BIC as the optimal model parameter.

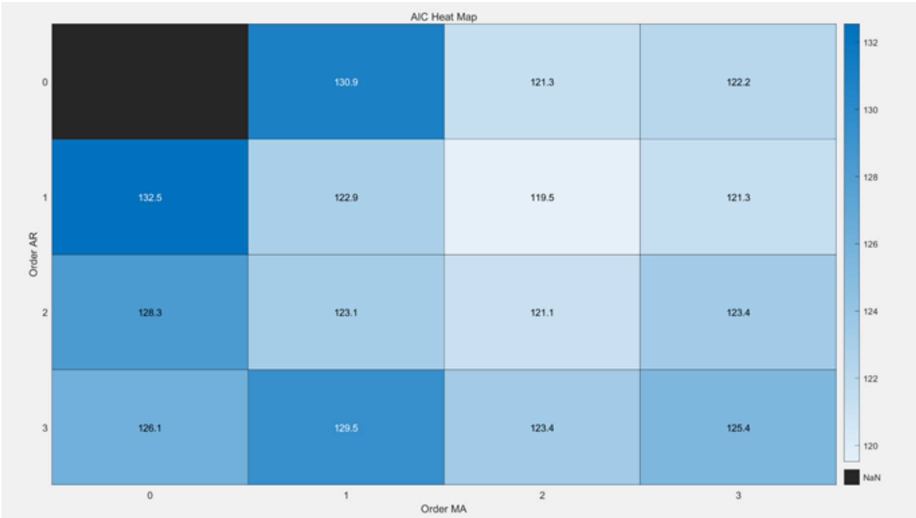


Figure 7: AIC criterion heat map

The estimated ARIMA model is diagnosed to check whether the model's residuals conform to the white noise hypothesis. Common diagnostic methods include checking the autocorrelation function of the residual sequence, partial autocorrelation function, normality and stationarity of the residual.

Here the absolute and relative errors are used. Below is a comparison of the predicted and actual values. It can be seen that the fit is relatively good.

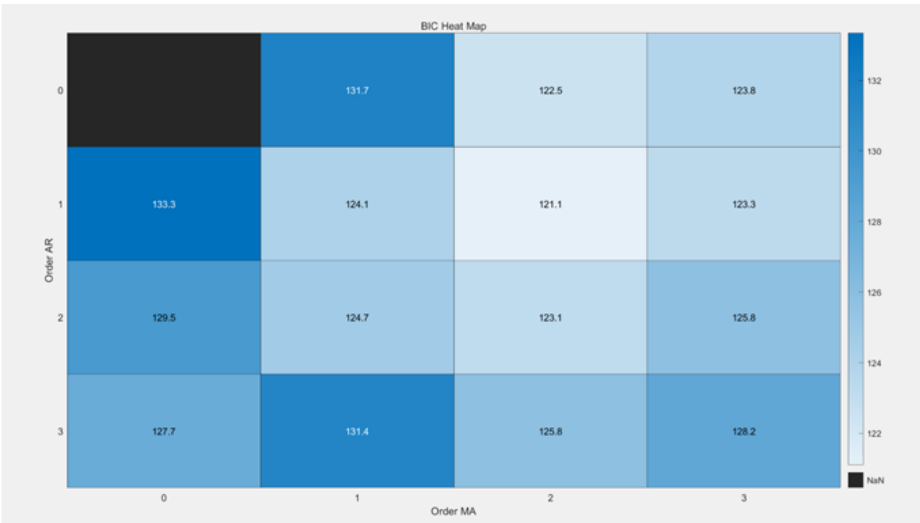


Figure 8: BIC criterion heat map

It can be seen from the figure that when AR is the first order and MA is the second order, AIC and BIC are the lowest, so p=1, q=2 can be selected to establish ARIMA (1,1,2) model for prediction. The prediction results are shown in the figure below.

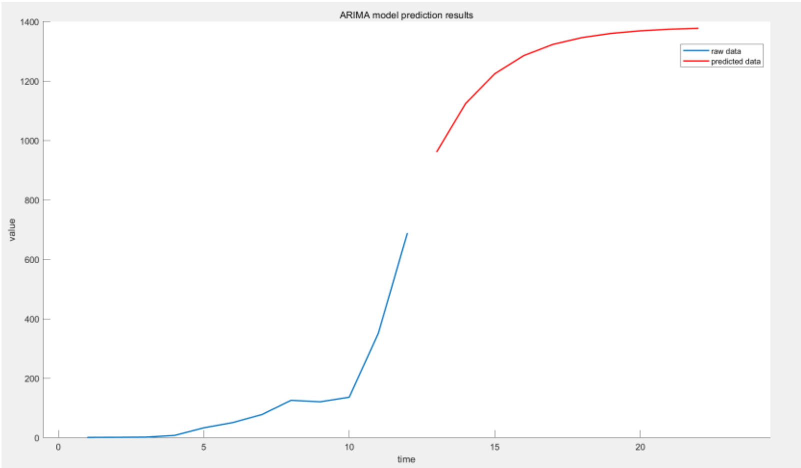


Figure 9: ARIMA model prediction results

5.2.2 Model diagnosis

Diagnose the estimated ARIMA model to check whether the model's residuals conform to the white noise hypothesis. Common diagnostic methods include checking the autocorrelation function of the residual sequence, partial autocorrelation function, normality and stationarity of the residual.

Here the absolute and relative errors are used. Below is a comparison of the predicted and actual values. It can be seen that the fit is relatively good.

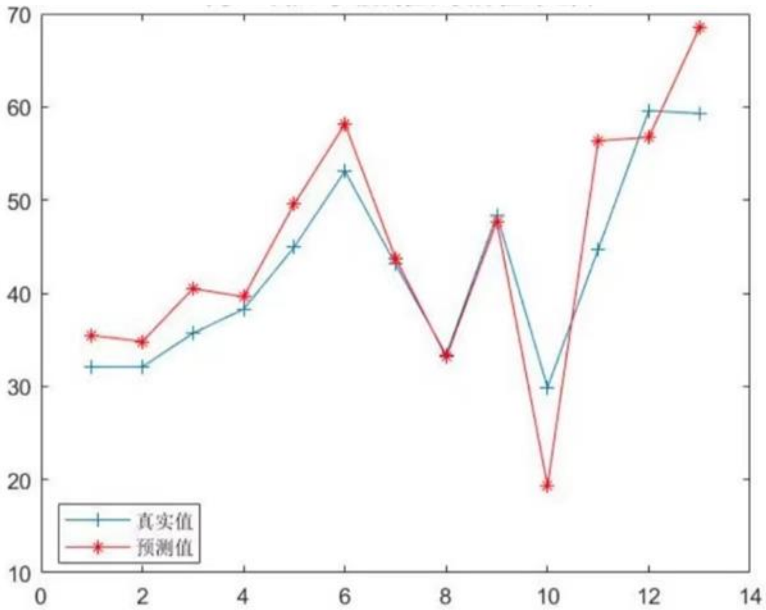


Figure 10: Comparison of predicted and actual values

5.2.3 Predicted data

The ownership and market share of new energy vehicles will be predicted by the same method, and the final results are as follows:

Time	New energy vehicle sales forecast (10,000 units)	Predicted value of vehicle ownership (10,000 units)	Predicted market share of new energy vehicles (%)
2023	960.600	1676.2032	20.78
2024	1124.281	1922.174	20.51
2025	1224.467	2288.3772	24.77
2026	1285.788	2534.3479	23.14
2027	1323.321	2900.551	20.21
2028	1346.294	3146.5217	22.88
2029	1360.355	3512.7247	24.22
2030	1368.962	3758.6953	21.36
2031	1374.230	4124.8983	21.47
2032	1377.454	4370.8689	23.86

It can be seen from the forecast results that the development of new energy electric vehicles in China in the next 10 years will still show an upward trend, but the rate will gradually decline.

5.3 Establishment and solution of Problem 3 model

5.3.1 Data collection

Collected data related to global traditional automobile sales, as shown in the following table.

Table 1: Global traditional automobile sales related data

Year	Global conventional vehicle sales (units)	Number of new energy vehicles (10,000)	Global sales of electric vehicles (unit: million)	Number of new energy vehicles in China (unit: million)
2013	57523750	3.35	0.105	0.100
2014	60951075	8.34	0.292	0.135
2015	62729525	32.82	0.545	0.340
2016	66718210	72.85	0.784	0.670
2017	68079275	124.87	1.213	1.032
2018	68225850	208.82	1.940	1.264
2019	65674575	308.86	2.260	2.582
2020	56239680	408.80	3.218	4.883
2021	57991560	518.79	6.716	7.798

2022	57927740	628.80	10.514	13.090

Using the above data set to study the impact of new energy electric vehicles on the global traditional energy vehicle industry, we construct a multiple regression model using the fitlm function in MATLAB. In this model, global traditional vehicle sales act as the dependent variable (response variable), while global electric vehicle sales and China's NEV ownership are independent variables (explanatory variables).

5.3.2 Model analysis

The solution results of fitlm function are shown below.

$$\begin{cases} y_1 = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 \\ \xi \sim N(0, \sigma^2) \end{cases}$$

Linear Regression Model:

y ~ 1 + x1 + x2

Coefficient Estimates:

Estimate SE tStat pValue

___________ the......

Intercept 6.2203e+07 1.5928e+06 39.053 1.8794e-09

x_1 6.6427e+06 2.8832e+06 2.304 0.054671

X_2-5.7446e +06 2.264e+ 06-2.5373 0.038815

Number of Observations: 10, Degrees of Freedom Error: 7

Root Mean Squared Error: 3.45e+06

R-Squared: 0.582, Adjusted R-Squared: 0.462

F-Statistic (Constant Model): 4.86, p-value = 0.0474

Linear regression model results:

$$y_1 \approx 6.22 \times 107 + 6.65 \times 106 \times x_1 - 5.74 \times 106 \times x_2$$

This model reveals the relationship between NEV sales (x1) and China's NEV ownership (x2) and global traditional car sales (y1). According to the estimated coefficient of the model, for every one million additional global electric vehicle sales, the total traditional vehicle sales may increase by about 6,448,700 on average. Notably, this result has a P-value of 0.054, which is slightly higher than the traditional significance level of 0.05.

At the same time, an increase of one million new energy vehicle ownership in China may reduce global conventional vehicle sales by an average of about 5,585,600 units, and this effect is statistically significant (p value of 0.0388). This suggests that the expansion of China's NEV market seems to have had a negative impact on global traditional vehicle sales, and more in-depth research is needed to understand the root cause of this correlation.

The R-square value of the model is 0.582, which means that our explanatory variable can explain 58.2 percent of the variation in global traditional vehicle sales to some extent. However, after taking into account the degree of freedom of the model, the adjusted R-square is 0.456, indicating that the explanatory power of our explanatory variable to explain the variation decreases. This may be because other factors in the model are not accounted for, or more data is needed to more fully explain changes in global conventional vehicle sales. A p-value of 0.0474 for the F statistic means that our model is statistically more effective at predicting global conventional car sales than a constant model with no explanatory variables. This is a positive sign that our model is better able to capture changing trends in sales after accounting for explanatory variables.

Overall, our model points to an increase in NEV sales that could have an impact on global conventional vehicle sales

Has a positive impact, while an increase in NEV ownership in China may have a negative impact on global traditional vehicle sales

To impact. However, due to the small sample size (only 10 observations), we need to interpret these results with caution and be aware of the need to validate in a larger sample.

To visually demonstrate these relationships, we plotted line plots, as shown below:

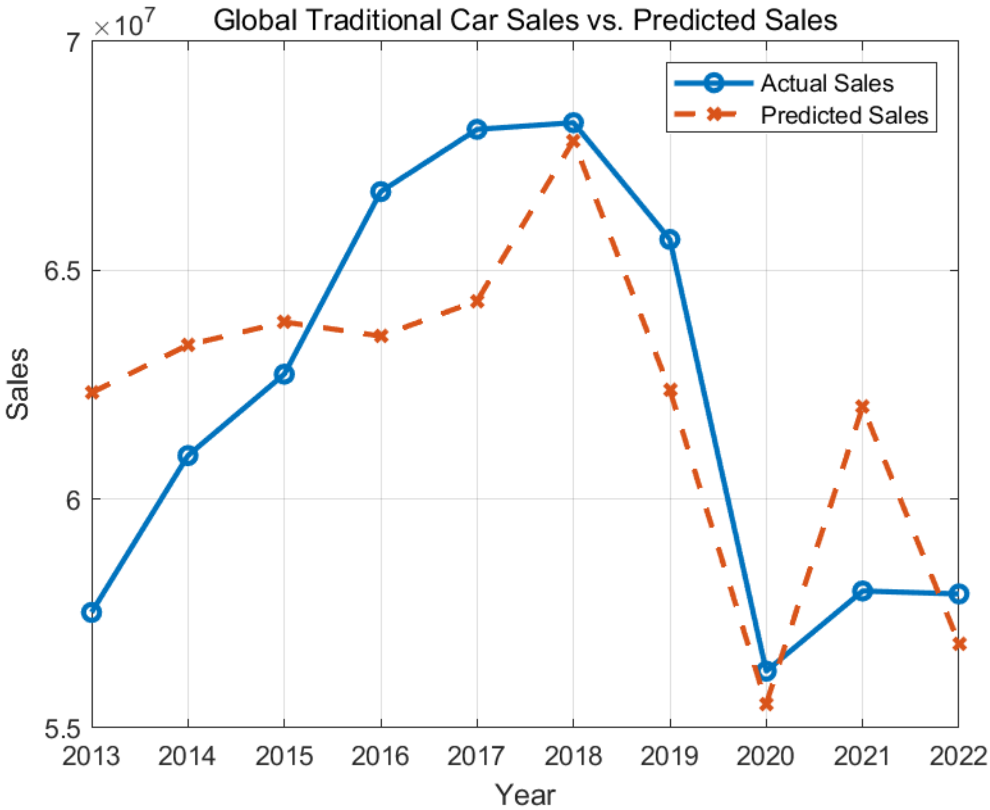


Figure 1: Global Traditional Car Sales vs. Predicted Sales

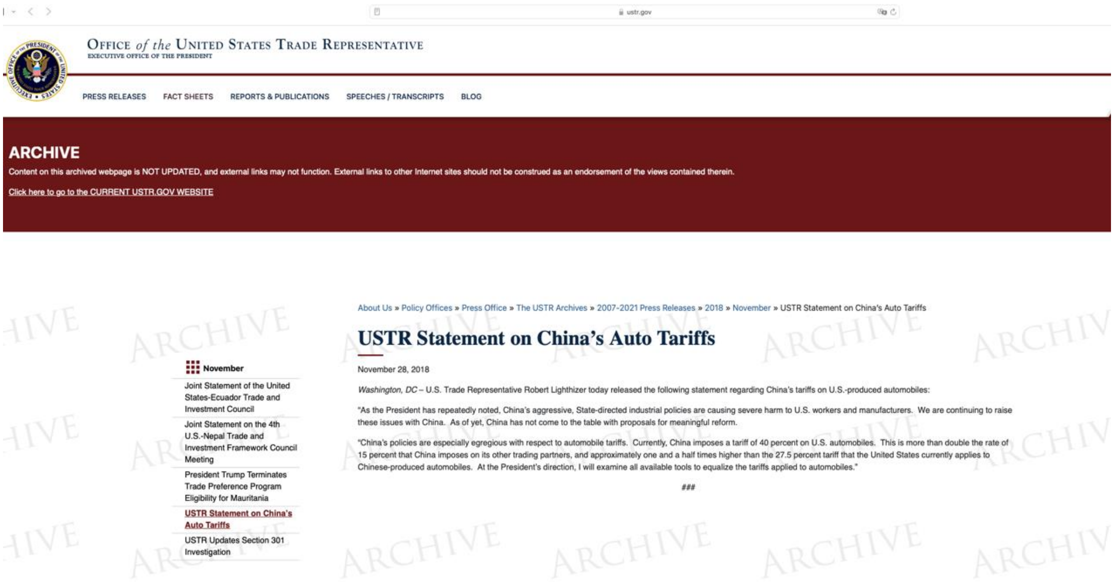
5.4 Establishment and solution of Problem four model

Through literature survey, it is found that foreign countries have not formulated policies specifically aimed at hindering the development of new energy electric vehicles in China. However, countries have adopted different strategies to deal with the gradual growth of Chinese electric vehicle manufacturers. The United States, in particular, has taken a distinctly protectionist stance when dealing with Chinese EVs.

Under President Donald Trump, the United States has imposed heavy taxes of up to 27.5 percent on cars made in China. The tariff, along with protective tax credits in President Joe Biden's "Inflation Reduction Act" that favor car and battery production in North America, has created a huge barrier for Chinese automakers to enter the US market.

Specifically, under the leadership of President Biden, the US government has passed a number of bills and policies aimed at improving the competitiveness of domestic electric vehicle and battery production. Such measures have not only restricted market access for Chinese electric vehicles, but also increased support for local industries in North America, forming a pattern that protects national interests while limiting international competition.

More detailed information on this issue can be found on the website of the Office of the US Trade Representative.



On this website, there are statements about the measures taken by the United States with respect to the Chinese auto industry, providing us with the opportunity to learn more in depth. This shows that although foreign countries have not promulgated clear policies for China's new energy electric vehicles, in practice, countries' protectionist tendencies towards their own industries are still obvious.

The United States formally implemented a 27.5 percent tariff on Chinese-made cars in November 2018, a decision that drew wide attention at the time. For this policy change, we will use data from before November 2018 to make projections and compare them with actual data. In view of the lack of a large number of relevant indicators, we choose to use the LSTM (Short Term Memory Network) model for prediction, in order to be able to portray the future situation to a certain extent before the policy is implemented.

Finally, the forecast comparison chart is shown in the figure below:

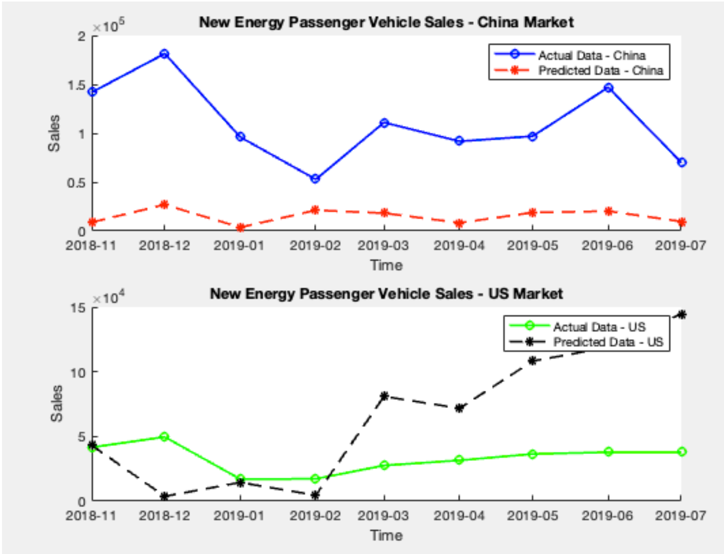


Figure 1: Sales of new energy passenger vehicles in the Chinese market and the US market

By carefully observing the comparison of the line chart, we can draw the following conclusions:

In terms of the Chinese market, after the implementation of the tariff policy, our sales forecast shows that the sales of new energy passenger vehicles are far lower than the actual sales. This raises an interesting question, which is that the tariff policy does not appear to have significantly curbed NEV sales growth in the Chinese market. Alternatively, other factors in the market, such as internal incentive policies, technological advances or changes in consumer preferences, may have outweighed the potential negative effects from the tariff policy.

When it comes to the US market, although the forecast figures are similarly lower than the actual sales figures, the difference between the two is not as significant as in the Chinese market. This could indicate a relatively limited impact of tariff policy on the US market, or it could equally be influenced by other market dynamics.

Overall, sales of new energy vehicles in the Chinese and US markets have not shown the predicted downward trend. This suggests that the growth momentum of the market may be enough to offset the potential negative impact of trade policies. However, it is important to note that such an analysis is only an observation based on limited data points and requires more data and in-depth market analysis to confirm it. Moreover, such an analysis cannot prove causation alone, as market dynamics are the combined result of multiple factors.

5.5 Establishment and solution of the model of Problem 5

5.5.1 Establishment and solution of model

The promotion of new energy electric vehicles in cities is a sustainable development measure aimed at reducing the adverse impact of traditional fuel vehicles on the environment. The purpose of this paper is to evaluate the potential impact of the electrification of new energy electric vehicles on the urban ecological environment through mathematical modeling and linear regression analysis.

To analyze the impact of urban new energy electric vehicles on the ecological environment, the potential impact on carbon emissions is analyzed using the indicators of new energy vehicle ownership, sales volume, market size, number of enterprises, number of patent applications, industrial chain scale, number of charging piles and charging infrastructure coverage. Therefore, this section is expected to establish a regression model of carbon emissions to the other nine indicators. The linear regression model is initially tried, and the results are as follows:

The number of observations is 8 and the degree of freedom of error is 0. The R square of the model is 1 and the adjustment R square is negative infinity. The F statistic (corresponding to the constant model) is 0 and the p-value is NaN.

These indicators indicate that there may be a problem with the model that needs to be further checked and improved. Based on such results, we introduced Lasso regression for solving and the results are shown below.

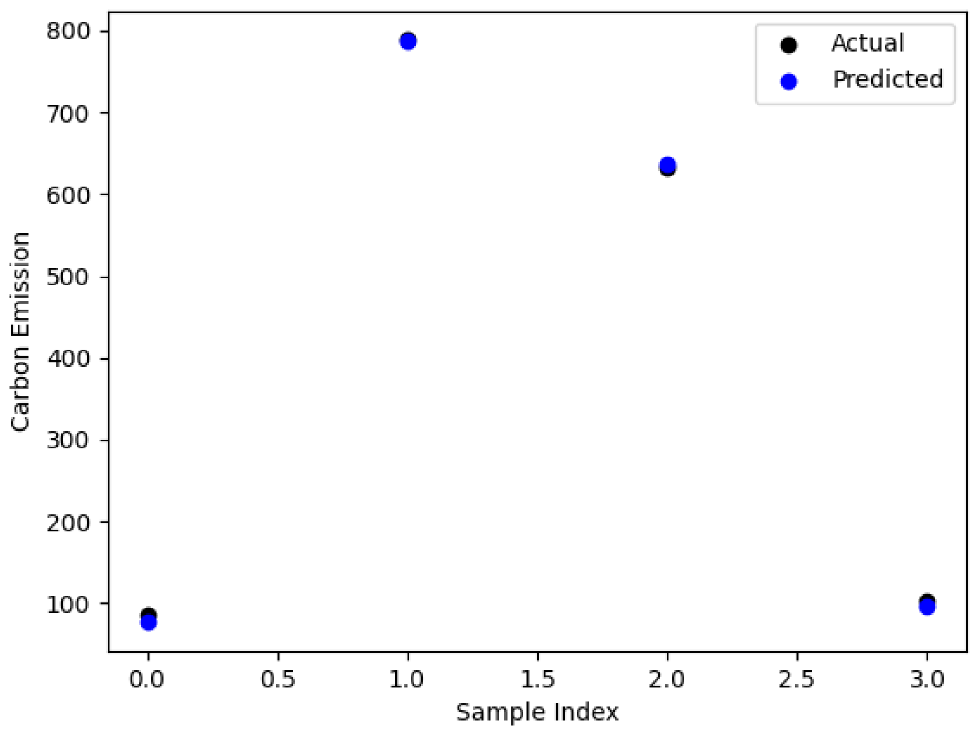


Figure 5.1 Scatter plot of actual value and predicted value

Above, the X-axis represents the index of the sample, which is used to view the performance of the model on the entire test set. In the scatter plot, the horizontal axis is the index of the sample, and the vertical axis is the actual carbon emission value and the model prediction value of the corresponding sample. This allows you to visually compare the difference between the actual value and the predicted value.

Model the relationship between EV industry related features and carbon emissions by using Lasso regression models in python code, and evaluate the performance of the model on the test set.

The following is the data obtained together:

Table 1: Regression coefficients

trait	Coefficient
Number of charging piles for new energy vehicles (10,000)	48.3827375
New energy vehicle ownership (10,000 units)	0.000257831225
Amount of subsidies for new energy vehicles (RMB 1 billion)	0.0669127124
Coverage of charging infrastructure for new energy vehicles (%)	0.0611641339
Number of new energy vehicle patent applications (items)	0.00277263754
New energy vehicle industry chain scale (home)	0.057791993
Market size of new energy vehicles (100 million yuan)	0.248831868
Sales of new energy vehicles (10,000 units)	1.34609589

Table 2: Model performance indicators

Indicators	value
MSE	30.13922919663696
R^2 score	0.9996937180819192

Eventually, Through the results, we can see the number of new energy vehicle charging piles (10,000), the number of new energy vehicles (10,000), the amount of new energy vehicle subsidies (one billion yuan), the coverage rate of new energy vehicle charging infrastructure (%), the number of new energy vehicle patent applications (items), the scale of new energy vehicle industry chain (home), the size of new energy vehicle market (100 million yuan), and new energy The regression coefficients of these features such as source vehicle sales (10,000 units), which represent the impact or contribution of each feature to the prediction of carbon emissions. A positive coefficient means that an increase in the feature value correlates with an increase in carbon emissions, while a negative coefficient indicates the opposite relationship. The size of the coefficient indicates the strength of the association. To visualize the results, the model results were plotted as follows:

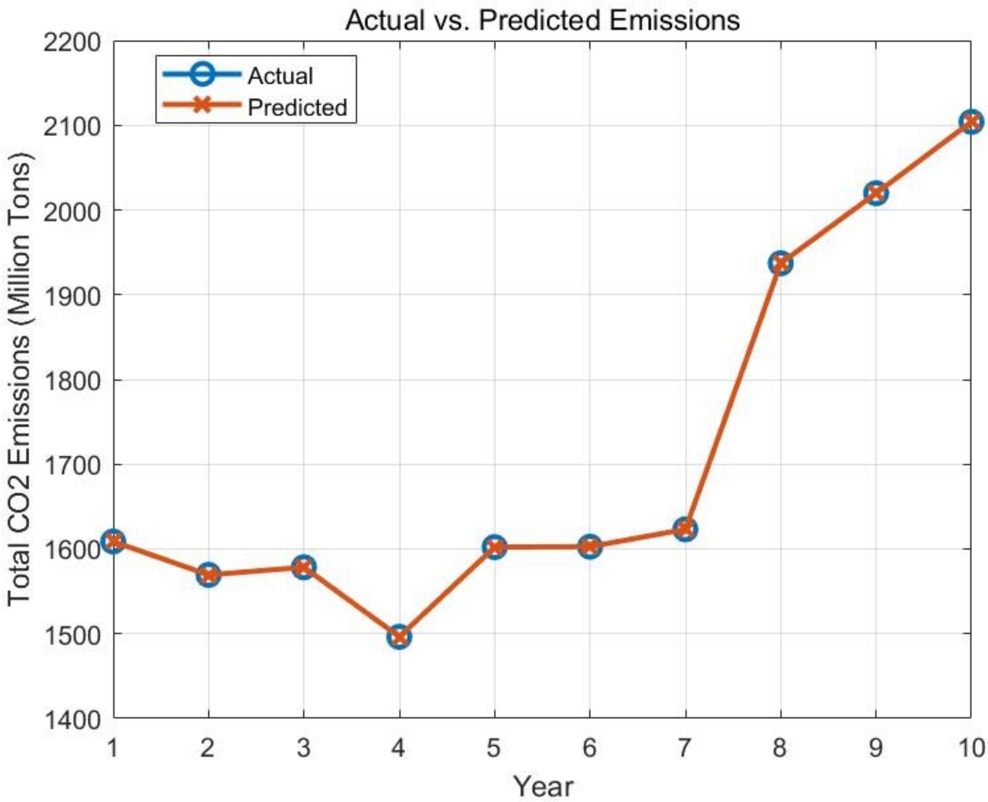


Figure 5.2 Comparison of actual and predicted carbon emissions

This graph shows the comparison between the actual total carbon emissions for each year (represented by a circle) and the total carbon emissions predicted by the linear regression model (represented by a cross). By comparing the actual and predicted values, you can visually see how well the model fits. Ideally, the difference between the actual value and the predicted value should be as small as possible, indicating that the model is capturing trends in the data more accurately.

5.5.2 Detection of the model

Next, the histogram of the residual analysis is used to check whether the residual of the model conforms to the normal distribution. The residuals are the difference between the actual value and the predicted value of the model, and the residuals of the normal distribution help verify the rationality of the model.

5.6 Solution to problem 6

Dear fellow citizens,

Today, we stand at a crucial moment in history, on the road to sustainable living. The global pursuit of new energy electric vehicles has gone beyond the wave of fashion to become a profound change as we move towards cleaner air, a healthier environment and a new round of economic innovation. Around the world, the rise of electric vehicles (EVs) is significantly reducing our carbon emissions. Cities that were once shrouded in smog now show clearer skies. The low hum of electric engines has become the new melody of city life, replacing the cacophony of traditional gasoline engines.

The electric vehicle industry has made a remarkable contribution to our economy. Not only has it created lots of jobs and enabled new technologies to flourish, it has also led us towards energy self-sufficiency. It's not just about adopting a new mode of transport, it's about shifting the way we think and embracing a future where technology and ecology are symbiotic.

Together, let us support and celebrate the electric vehicle revolution. By choosing to drive electric cars, we are creating a greener planet for future generations.

In addition, the development of electric vehicles also brings a series of benefits. First, the maintenance cost of electric vehicles is relatively low. Since there is no traditional engine and transmission system, electric vehicles do not need to change parts such as oil and filters regularly, thus reducing maintenance costs. Secondly, electric vehicles also have lower operating costs. The price of electricity is more stable than that of fuel, and the cost of recharging an electric car is relatively low. In addition, electric vehicles can also use regenerative braking technology to convert braking energy into electricity and store it, further improving energy efficiency.

However, there are still some challenges we need to overcome in order to achieve the popularity of electric vehicles. The first is the construction of charging infrastructure. In order to facilitate users to charge, we need to build more charging piles and charging stations, and improve charging speed and efficiency. The second is the improvement of battery technology. At present, the range of electric vehicles is still limited, and the energy density and charging speed of batteries need to be further improved. Finally, there is consumer awareness and acceptance of electric vehicles. We

need to step up publicity and education to make more people aware of the advantages and potential of electric vehicles, so as to increase their market share.
All in all, the development of electric vehicles has brought us great opportunities and challenges. Let us work together to promote the flourishing development of the electric vehicle industry and create a better future for our children and grandchildren.
Best wishes.
[Name]
[Your relationship to the community/position]

6. Summary of the model

6.1 Advantages of the model

1. Multi-dimensional comprehensive analysis: The model integrates many aspects such as economy, society, market penetration and technological innovation, and provides a basis for a comprehensive understanding of the new energy vehicle market.
2. Multi-method comprehensive forecasting: It uses a variety of forecasting technologies such as regression analysis, gray forecasting and LSTM, which effectively improves the accuracy and reliability of the forecast.
3. Data-driven method: The model is based on a large amount of actual data and advanced data processing techniques, such as data crawler and interpolation methods, to ensure the comprehensiveness of the data and the accuracy of the analysis.
4. Comprehensive assessment of policy impact: External policy changes, such as tariff adjustments, are fully considered to assess the impact on the development of new energy vehicles, making the model closer to actual market dynamics.
5. Key consideration of environmental benefits: Taking carbon dioxide emissions as an evaluation index, the positive impact of new energy vehicles on the ecological environment is emphasized, highlighting the importance of environmental protection.
6. Clear model assumption framework: Clear model assumptions are set up to provide direction and analytical framework for problem solving, helping to focus on key variables and logical relationships.

6.2 Shortcomings of the Model

Data reliability limitations: The accuracy of the model is limited by the quality and integrity of the available data. Biased or incomplete data collection may affect the accuracy of the results.
Simplified assumptions: Models may be based on simplified or idealized assumptions to facilitate analysis. These assumptions may deviate somewhat from the actual situation.
Unconsidered external factors: The model may not fully consider all external influencing factors, such as macroeconomic fluctuations, political changes, etc., which may affect the stability of the forecast results.

Static assumption: Factors affecting the development of new energy vehicles may change over time, but the model may fail to adapt to these dynamic changes.
Regional limitations: If the data is mainly from a specific region, such as Tianjin, then the conclusions of the model may not be easily generalized to other regions or countries.
Unknown technological changes: Technological innovation in the NEV industry is rapid, and the model may not be able to predict the impact of future technological changes on the market.

6.3 Model Promotion

The model performs well in comprehensiveness and multi-dimensional analysis, and is suitable for similar market environment and policy research. However, limited by data and assumptions, the direct application of the model may be limited to regions with similar economic and technological backgrounds. In addition, models may have some limitations in adapting to rapidly changing technological and market conditions. Therefore, it is necessary to regularly update data and reevaluate assumptions in the face of the evolving NEV market. Overall, while the model provides valuable insights into the NEV market, its limitations need to be considered and adjusted and updated accordingly when making cross-regional or long-term promotion applications.

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