Team Number :	apmcm2311406
Problem Chosen :	C

Analysis and Future Development Trend of New Energy Vehicles Based on Regression Analysis and Prediction Model

Summary

Since 2011, the Chinese government has actively promoted the development of new energy electric vehicles and formulated a series of preferential policies, opening a new chapter for this emerging industry. In the past decade, the new energy electric vehicle industry has experienced tremendous development, gradually becoming another business card that showcases China's innovation strength after the "China High Speed Rail". This article establishes multiple models to quantitatively evaluate the current development status of the industry and predict future trends, providing a strong basis for us to deeply understand the growth momentum and potential opportunities of this industry.

For question one,we have decided to use the change in sales volume of new energy electric vehicles as an indicator to observe the development of new energy electric vehicles. Factors that affect the sales volume of new energy electric vehicles generally include the number of charging stations in the country, the installed capacity of new energy electric vehicle batteries, the investment amount in the new energy electric vehicle industry chain, national carbon emissions, and per capita gross national income, The problem is a typical dependent variable with multiple independent variables, so we decided to use a multiple linear regression model to solve the problem. For the data we collected, we first visualized and analyzed it, and then used the multiple linear regression model to solve the problem. It was found that the impact of new energy electric vehicles is mainly influenced by the number of new energy electric vehicle charging stations and the installed capacity of new energy vehicle power batteries in the country.

For question tow ,it’s to predict the impact of the development of new energy electric vehicles in China in the next 10 years, based on the sales volume of new energy vehicles. To predict future development, predictive models should be used, so

we adopt time series prediction models. Firstly, train the model, divide the collected data into training and testing sets, and verify the stationarity of the data. When encountering unstable data, perform differential operations on it to convert it into a stationary time series. Then give the model an order, and finally diagnose the model.

For question third,it’s about analyzing the impact of one thing on another, which usually involves analyzing the correlation between some performance indicators of the two. This question mainly studies the relationship between new energy vehicles and global traditional energy vehicles, and can identify several factors related to them for correlation analysis. Study the impact of new energy electric vehicles on the global traditional energy vehicle industry. We extracted three relevant factors: global oil price changes (indirectly reflecting the global use of traditional energy vehicles), research and development of traditional energy technologies, and global sales of new energy vehicles. Perform Pearson correlation coefficient test first, then further conduct causal test, and finally establish AR.

For question four, the question asks us to analyze the impact of some foreign policies on the development of new energy electric vehicles in China. We have decided to use comparative analysis, By comparing the development trends of new energy electric vehicles in China before the release of relevant targeted policies from abroad with the development of new energy electric vehicles in China after the release of relevant policies from abroad, and then using a grey prediction model to predict the development data of new energy electric vehicles in China in the past two years based on existing data, the predicted values are compared with the actual collected development data of new energy electric vehicles, Through the analysis of the results, it can be seen that the development of new energy electric vehicles in China has been somewhat affected after the release of relevant policies in foreign countries. However, the actual values still exceed the predicted values, indicating that the impact of foreign targeted policies on the development of new energy electric vehicles in China is negligible. The rapid development of new energy electric vehicles in China has become an inevitable trend.

For question five, we can consider finding the total number of various types of cars in the country and reducing it to a lower level based on population proportion and calculate the current energy consumption and carbon emissions based on the car ownership of a population of 100000. Then it is electrified, and the energy consumption and carbon emissions after electrification are calculated to obtain the emission reduction effect of new energy electrification. Analysis shows that carbon emissions have significantly decreased after urban electrification, with an overall decrease of 28%.

For question six, write an open letter to the public based on the above conclusion.

Contents

目录

一、Problem Restatement

1.1 Question Background

At present, new energy vehicles mainly include hybrid electric vehicles, pure electric vehicles, fuel cell electric vehicles, and other types. The common feature of these car models is the use of electricity or other clean energy sources as power, effectively reducing carbon emissions and air pollution. In addition, new energy vehicles also have the advantage of adjusting the peak electricity demand, which has a positive effect on alleviating power shortages and optimizing energy structure.

In recent years, new energy vehicles have gained widespread love and strong support from global consumers and governments around the world. Especially in China, since 2011, the government has vigorously promoted the development of new energy vehicles and formulated a series of preferential policies, including fiscal subsidies, tax reductions, priority registration, etc., which have effectively promoted the rapid development of the new energy vehicle industry.

After several years of efforts, China's new energy vehicle industry has achieved significant development results. Not only has the production and sales volume been increasing year by year, but the technological level is also constantly improving. At the same time, the popularization and application of new energy vehicles have played a positive role in improving urban environment and promoting the development of green transportation. Nowadays, new energy vehicles have become another shining symbol of China after the "China High Speed Rail".

Looking ahead to the future, with the increasing awareness of environmental protection and energy conservation among consumers, as well as strong government support for the new energy vehicle industry, the market share of new energy vehicles in the global market will continue to grow. Meanwhile, the continuous advancement of technology will also bring more possibilities for the development of new energy vehicles. Therefore, we have reason to believe that new energy vehicles will occupy a more important position in the future automotive market

1.2 Question Raising

Question 1: Analyze the main factors that affect 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 industry development data on China's new energy electric vehicles, 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 policies targeted to resist the development of new energy electric vehicles in China. Establish a mathematical model to analyze the effects of these policies on the development of new energy electric vehicles in China.

Question 5: Analyze the impact of the electrification of new energy electric vehicles (including electric buses) in cities on the ecological environment. Assuming that there is an urban population of 1 million, provide the calculation results of the model.

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

二、Problem Analysis

2.1 Analysis of problem one

For question one:

1.What are the factors that affect the development of new energy vehicles and describe and analyze their impact on the development of new energy vehicles? Considering that there are often many factors that affect the development of new energy vehicles.

2.For example, the number of charging stations in our country can affect the willingness of residents to purchase new energy vehicles, and the total national income may also affect the purchase of new energy vehicles by residents, or some factors such as policies, markets, technology, and environment.

3.So here, I have decided to measure the development of new energy vehicles using the sales volume of new energy vehicles as the dependent variable, and to use factors such as the number of charging stations, the installed capacity of new energy vehicle power batteries, the investment amount in the new energy vehicle industry chain, China's carbon emissions, and per capita gross national income as independent variables to conduct a multiple linear regression model.

2.2 Analysis of problem two

For question two:

1. The question requires collecting data on the development of China's new energy electric vehicle industry, in order to predict the development of the industry in the next 10 years. To predict future development, predictive models such as ARIMA

or GM (1,1) models should be used.

2. We use the ARIMA model, first train the model and check the stationarity of the data, then determine the order of the model according to AIC criteria, and finally diagnose the model

2.3 Analysis of problem three

For question three:

1. Analyzing the impact of one thing on another usually involves analyzing the correlation between some performance indicators of the two

2. This question mainly studies the relationship between new energy vehicles and global traditional energy vehicles, and can identify several factors related to them for correlation analysis.

3. This problem first uses Pearson correlation coefficient to obtain the relationship between the two, then uses causal correlation to screen for relevant factors, and finally uses vector autoregression.

2.4 Analysis of problem four

For question four:

1. It requires us to analyze the impact of a series of targeted policies formulated by some countries on the development of new energy electric vehicles in China. Here, we have decided to use the development data of new energy electric vehicles in China before the release of targeted policies to predict the development data of new energy electric vehicles in the following years.

2. Then search for actual data to compare and analyze the predicted data with the actual data, Furthermore, we can understand the impact of targeted foreign policies on the development of new energy electric vehicles in China.

2.5 Analysis of problem five

For question four:

1. Find data on the number of various types of cars in the country and calculate the number of cars in a city with a population of 1 million based on the population ratio.

2. Calculate the current energy consumption and carbon emissions of these cars. This can be obtained by estimating the energy consumption and carbon emission rate of each vehicle model, and then multiplying it by the number of that vehicle model.

3. Electrify these cars and calculate their energy consumption and carbon emissions after electrification. This can be estimated by multiplying the energy consumption and carbon emission rate of each electric vehicle model by the number of that model.

4. Compare the energy consumption and carbon emissions before and after electrification, and determine the emission reduction effect of new energy electric vehicle electrification.

2.6 Analysis of problem six

Based on the previous text, write an open letter

三、Symbol Description

Symbol	Description
Y	Sales of new energy vehicles
X_1	The number of charging piles for new energy vehicles
X_2	The installed capacity of power batteries for new energy vehicles
X_3	The amount of investment in the new energy vehicle industry chain
X_4	China's carbon emissions
X_5	Gross national income per capita
β	Parameters of the model
ε	Error terms
$x^{(0)}$	Primordial order
$x^{(1)}$	A new sequence after the original sequence is accumulated
r	The quotient of covariance and standard deviation
x_i	Sample data
$\bar{x}$	Sample average
σ_x	Sample standard deviation
Y(t)	Global sales volume of traditional energy vehicles
X(t)	The relatively relevant factors obtained
A(1)⋯A	Equally estimated coefficient matrix
B	Equally estimated coefficient matrix
e(t)	error vector

四、Establishment and solution of the model

4.1 Solving problem one

For the solution method of problem 1, we first searched for some data related to the development of new energy vehicles. Here, we selected the number of new energy vehicle charging stations, the installed capacity of power batteries for new energy vehicles, and the investment amount in the new energy vehicle industry chain The changes in national carbon emissions and per capita gross national income are some factors that affect the development of new energy vehicles. Based on these factors, we choose a multiple linear regression model to solve this problem.

The following is the data we have collected from various websites:

Figure 1 Related factor data

Year	Y	X_1	X_2	X_3	X_4	X_5
2013	1.8	2.1	0.8	6.2	43143	9880.87
2014	7.5	2.3	3.7	14.7	46971	9883.51
2015	33.1	5	15.7	75.1	49684	9655.12
2016	50.7	14	28	276.6	53516	9686.99
2017	77.7	21.4	36.4	451	59514	9777.01
2018	125.6	33.1	56.9	319.7	65246	10126.99
2019	120.6	51.6	62.4	297	69881	10217.32
2020	136.7	66.7	63.6	302	71253	10306.72
2021	352.1	114.7	154.5	832	80237	10407.06
2022	688.7	520	294.6	374.9	85698	10509.08

Then visualize the data as follows：

Figure 2 Sales of new erenge vwhicles

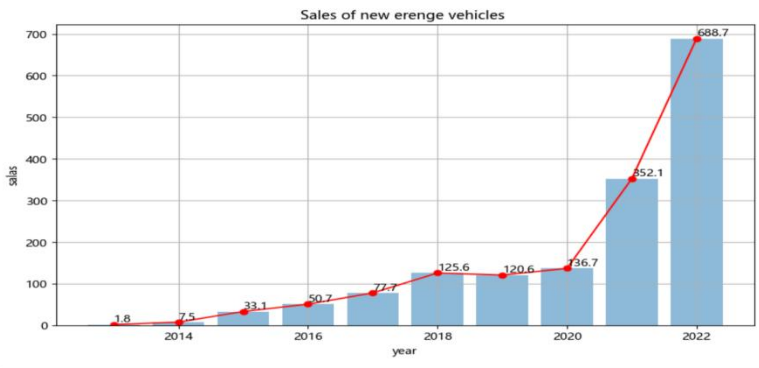


Figure 3 Installed capacity of power battery

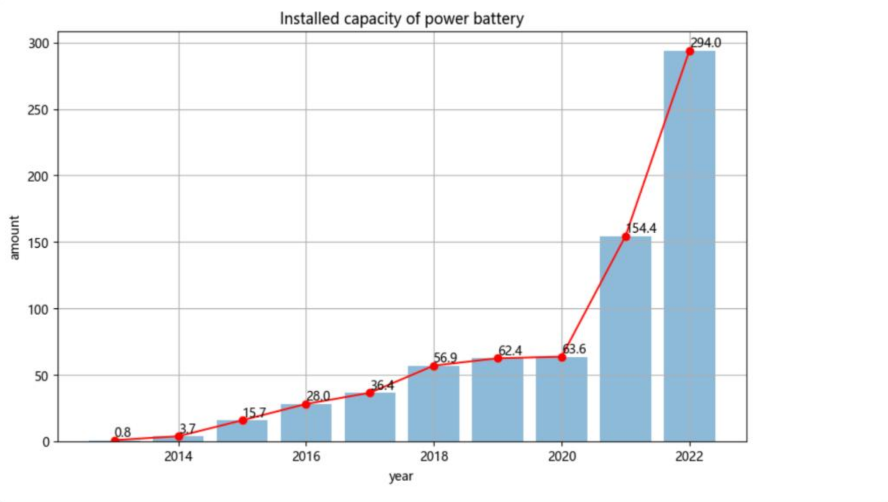


Figure 4 Storage quantity of charging pile

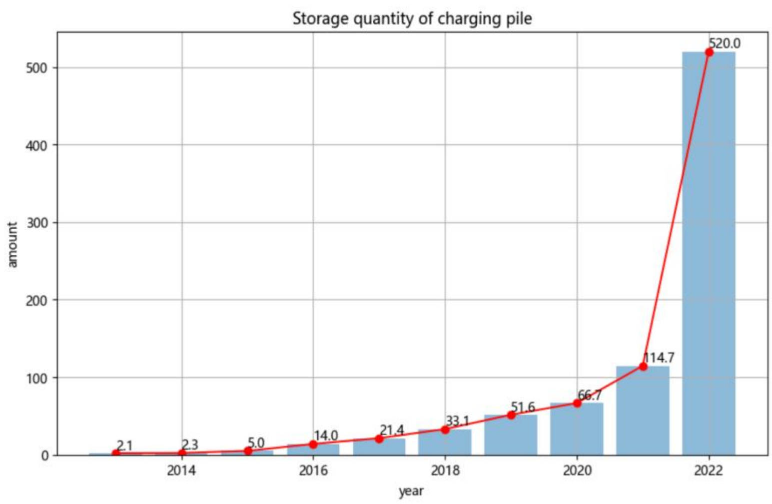


Figure 5 Investment amoun

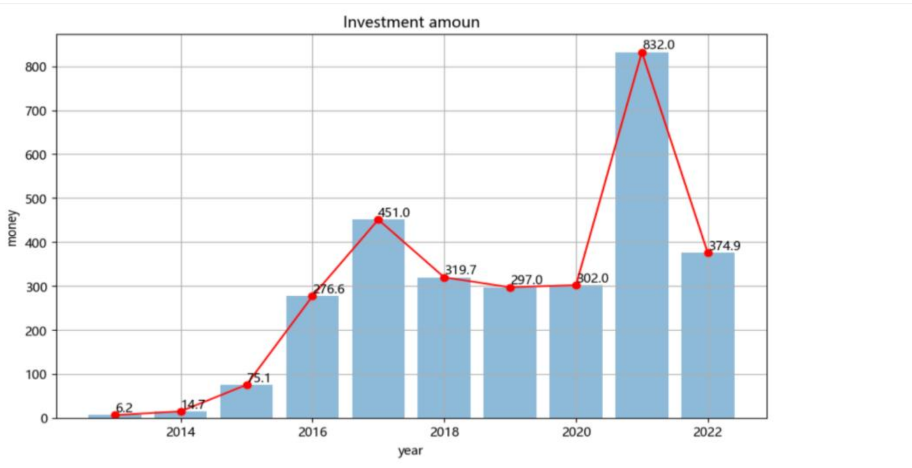


Figure 6 National carbon emissions

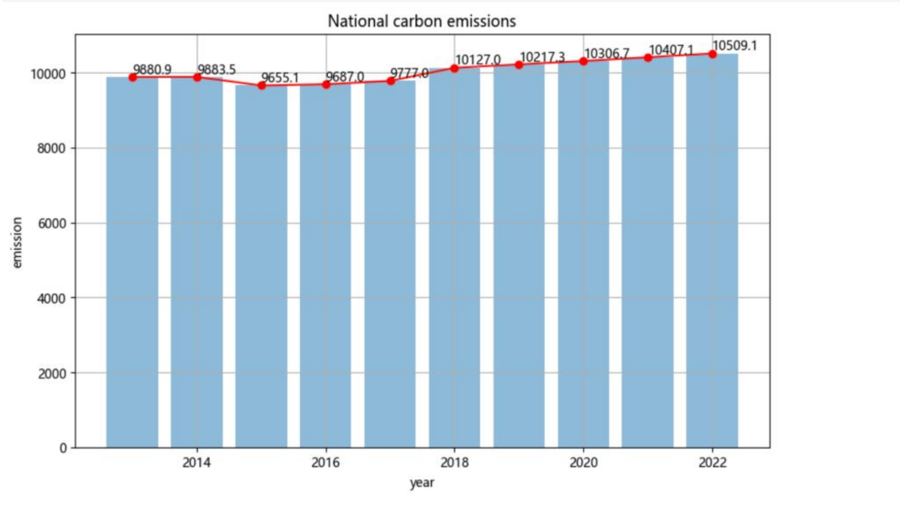
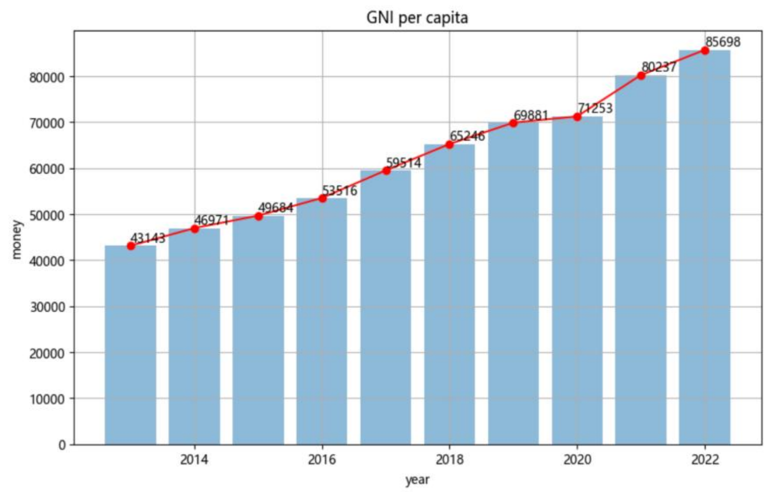


Figure 7 GNI per capita



Based on the above data, it can be preliminarily inferred that the development of the new energy vehicle industry is still in its early stages from 2013 to 2022. After 2022, the new energy vehicle related industry has begun to rapidly develop, with a surge in various indicators.

Next, we will establish a model and apply a multiple linear regression analysis model to further analyze the impact of the above factors on the development of new energy vehicles.

Firstly, let the dependent variable be y, and the five dependent variables are x_1,x_2,x_3,x_4,x_5 respectively. Their general form is:

$$Y=\beta_0+\beta_1 x_1+\beta_2 x_2+\beta_3 x_3+\beta_4 x_4+\beta_5 x_5+\varepsilon \tag{1}$$

Where y is the sales volume of new energy vehicles,x_1,x_2,x_3,x_4,x_5 are the above factors,β_0, β_1, β_3, β_4, β_5 are the model parameters, and are the error terms. Next, we will run the least squares estimation to calculate the parameters in the multiple linear regression model,β_0, β_1, β_3, β_4, β_5, to minimize the sum of squared residuals, namely

$$Q=\Sigma\ (y_i - \widehat{y_i})^2 = \Sigma\ (y_i - \widehat{\beta_0} - \widehat{\beta_1}x_1 - \widehat{\beta_2}x_2 - \widehat{\beta_3}x_3 - \widehat{\beta_4}x_4 - \widehat{\beta_5}x_5)^2 = \min \tag{2}$$

Obtained from multiple linear regression analysis using Python:

Figure 8 OLS regression Results

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                     1590.
Date:                Sun, 26 Nov 2023   Prob (F-statistic):           1.11e-06
Time:                        15:30:26   Log-Likelihood:                -29.231
No. Observations:                  10   AIC:                             70.46
Df Residuals:                       4   BIC:                             72.28
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept   -112.4086    190.696     -0.589      0.587    -641.867     417.049
x1             0.0346      0.155      0.223      0.834      -0.396       0.465
x2             2.3993      0.327      7.345      0.002       1.492       3.306
x3             0.0179      0.037      0.479      0.657      -0.086       0.122
x4            -0.0013      0.001     -1.956      0.122      -0.003       0.001
x5             0.0173      0.022      0.800      0.469      -0.043       0.077
==============================================================================
Omnibus:                        2.025   Durbin-Watson:                   3.087
Prob(Omnibus):                  0.363   Jarque-Bera (JB):                1.231
Skew:                          -0.809   Prob(JB):                        0.540
Kurtosis:                       2.423   Cond. No.                     5.49e+06
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 5.49e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Then output its analysis of variance table:

Figure 9 Analysis of variance

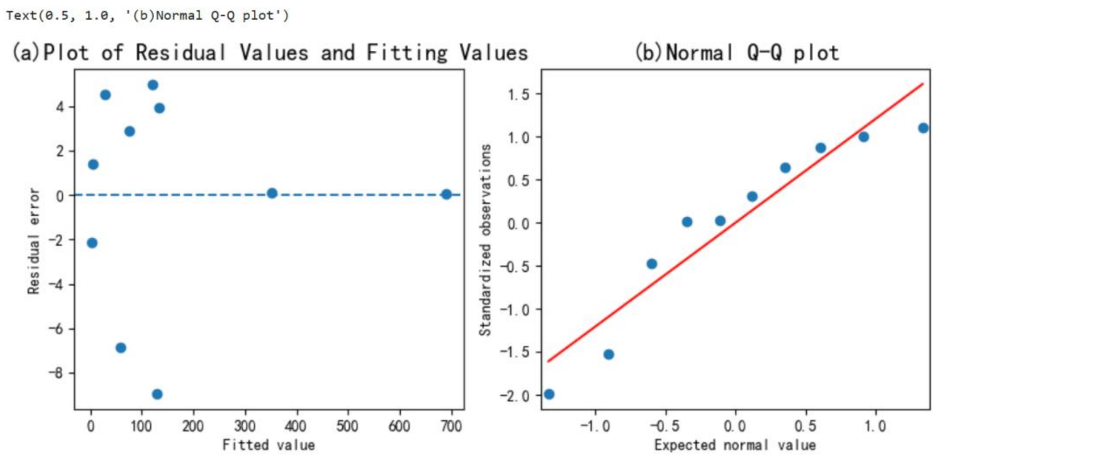
	df	sum_sq	mean_sq	F	PR(>F)
x1	1.0	371466.486926	371466.486926	7335.702258	1.113969e-07
x2	1.0	30909.173587	30909.173587	610.392868	1.592956e-05
x3	1.0	2.561244	2.561244	0.050579	8.330802e-01
x4	1.0	195.401629	195.401629	3.858782	1.209461e-01
x5	1.0	32.388962	32.388962	0.639616	4.686515e-01
Residual	4.0	202.552652	50.638163	NaN	NaN

Based on the above results, the estimated multiple linear regression equation is:

$$Y=-112.4086+0.03460x_1+2.3993+0.0179x_3-0.0013x_4+0.0173x_5 \tag{3}$$

Then, after testing and diagnosing the model, we obtain that:

Figure 10 Plot

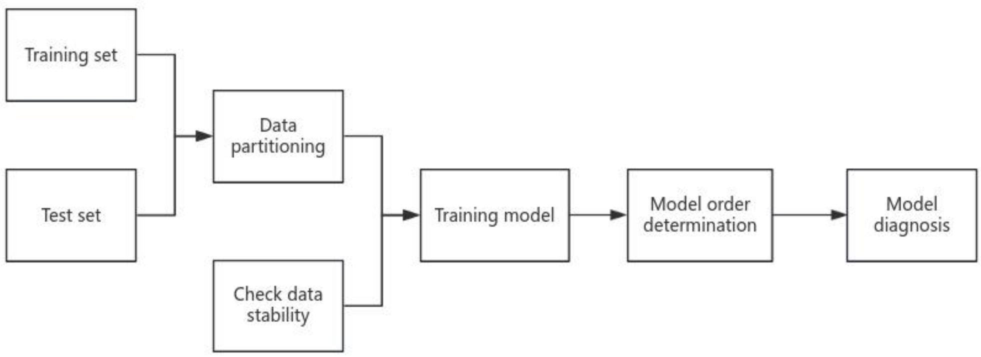


Based on the above results, it can be concluded that the development of new energy vehicles is influenced by the infrastructure of charging piles, as well as the installed capacity of new energy vehicle power batteries. Therefore, China should vigorously develop technology related to new energy vehicle power batteries and build more basic charging pile facilities.

4.2 Solving problem two

Predict the impact of the development of new energy electric vehicles in China in the next 10 years, based on the sales volume of new energy vehicles. Firstly, train the model well, divide the collected data into training and testing sets, and verify the stationarity of the data. When encountering data instability, perform differential operations on it to convert it into a stationary time series. Then give the model an order, and finally diagnose the model.

Figure 11The flowchart for question four



4.2.1training model

Divide the collected data into training and testing sets, and perform stationarity checks on the data. If the data is unstable, perform differential operations on the data to convert it into a stationary time series.

Figure 12 Sales Table of New Energy Vehicles

Time	Sales volume of new energy vehicles	Sales of pure electric vehicles	Sales of plug-in hybrid vehicles
2017/1	0.568	0.4978	0.0704
2017/2	1.7596	1.3919	0.3677
2017/3	3.112	2.5342	0.5778
2017/4	3.4361	2.857	0.5791
2017/5	4.53	3.853	0.677
2017/6	5.9	4.8	1.1
2017/7	5.6	4.4	1.2
2017/8	6.8	5.6	1.2
2017/9	7.8	6.4	1.4
2017/10	9.1	7.7	1.4
2017/11	11.9	10.2	1.7
2017/12	16.3	14.4	1.9
2018/1	4.0247	2.6753	1.1717
2018/2	3.442	2.3458	1.0962
2018/3	6.7778	5.2174	1.5602
2018/4	8.1904	6.4786	1.7062
2018/5	10.2	8.2	2
2018/6	8.4	6.2	2.2
2018/7	8.4	6	2.4
2018/8	10.1	7.3	2.8
2018/9	12.1	9.4	2.7
2018/10	13.8	11.1	2.7
2018/11	16.9	13.8	3.1
2018/12	22.5	19.3	3.2
2019/1	9.6	7.5	2.1
2019/2	5.3	4	1.3
2019/3	12.6	9.6	3

2019/4	9.7	7.1	2.6
2019/5	10.4	8.3	2.1
2019/6	15.2	12.9	2.2
2019/7	8	6.1	1.9
2019/8	8.5	6.9	1.6
2019/9	8	6.3	1.7
2019/10	7.5	5.9	1.6
2019/11	9.5	8.1	1.4
2019/12	16.3	14	2.1
2020/1	4.4	3.3	1.3
2020/2	1.2908	1.068	0.2228
2020/3	5.3	4	1.3
2020/4	7.2	5.1	2.04
2020/5	8.2	6.4	1.8
2020/6	10.4	8.2	2.1
2020/7	9.8	7.8	1.9
2020/8	10.9	8.8	2.4
2020/9	13.8	11.2	2.6
2020/10	16	13.3	2.7
2020/11	20	16.7	3.3
2020/12	24.8	21.1	3.7
2021/1	17.9	15.1	2.9
2021/2	11	9.2	1.7
2021/3	22.6	19	3.6
2021/4	20.6	15.8	3.5
2021/5	21.7	21.1	3.8
2021/6	25.6	21.1	4.4
2021/7	32.1	25.1	5.6
2021/8	32.1	26.5	5.6
2021/9	35.7	29.6	6.1
2021/10	38.3	31.6	6.71
2021/11	44.96	36.1	8.86
2021/12	53.1	44.8	8.24
2022/1	43.1	34.7	8.54
2022/2	33.4	25.8	7.53

2022/3	48.4	39.5	8.79
2022/4	29.9	23.1	6.8
2022/5	44.7	34.7	10
2022/6	59.6	47.6	12
2022/7	59.3	45.7	13.5
2022/8	66.6	52.2	14.4

4.2.2Model order determination

Then, based on the differential data and AIC criteria, determine the order of the model and select
q=2

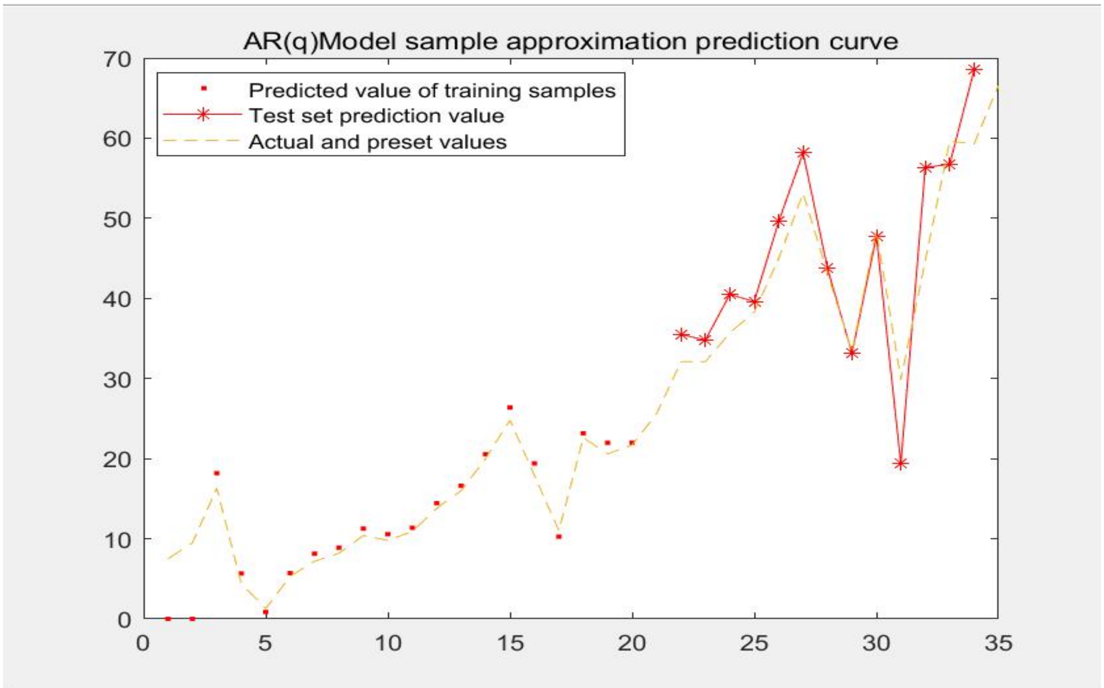
1x20 double

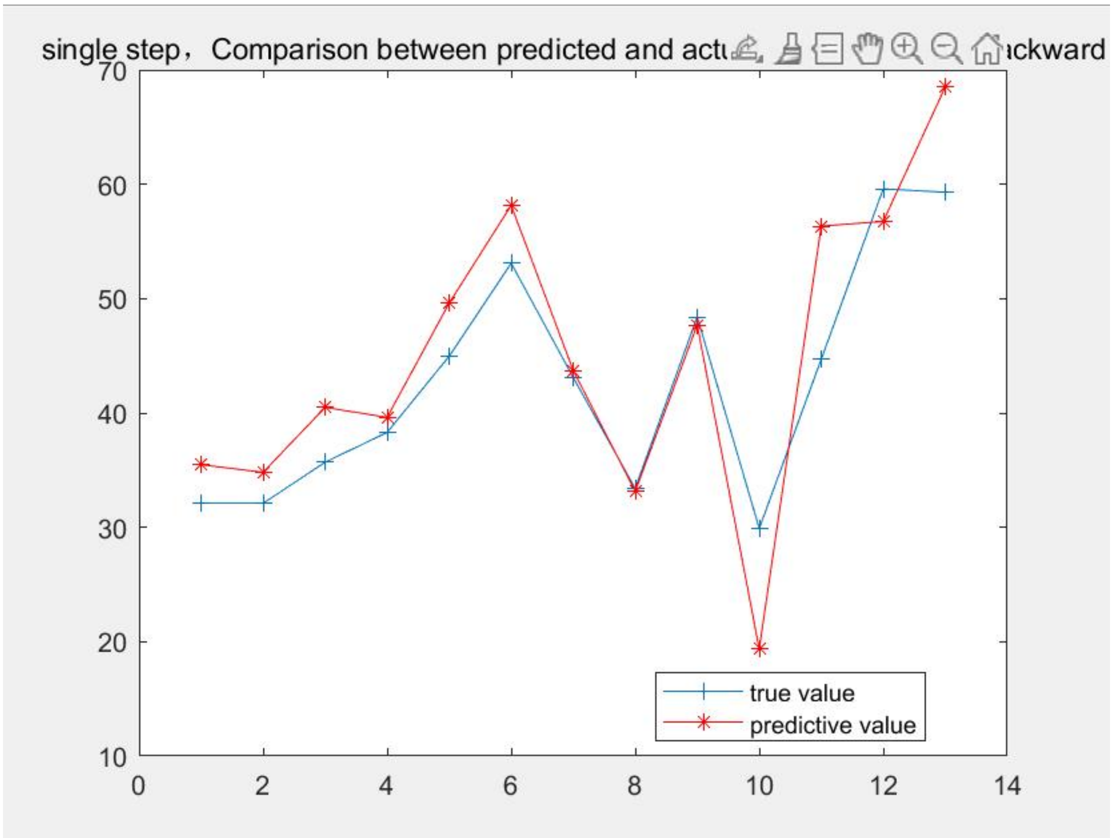
1	2	3	4	5	6	7	8	9	10	11
57.7765	42.4069	42.9293	44.8765	45.4827	48.1810	51.2155	54.4173	57.3492	60.7846	56.9691

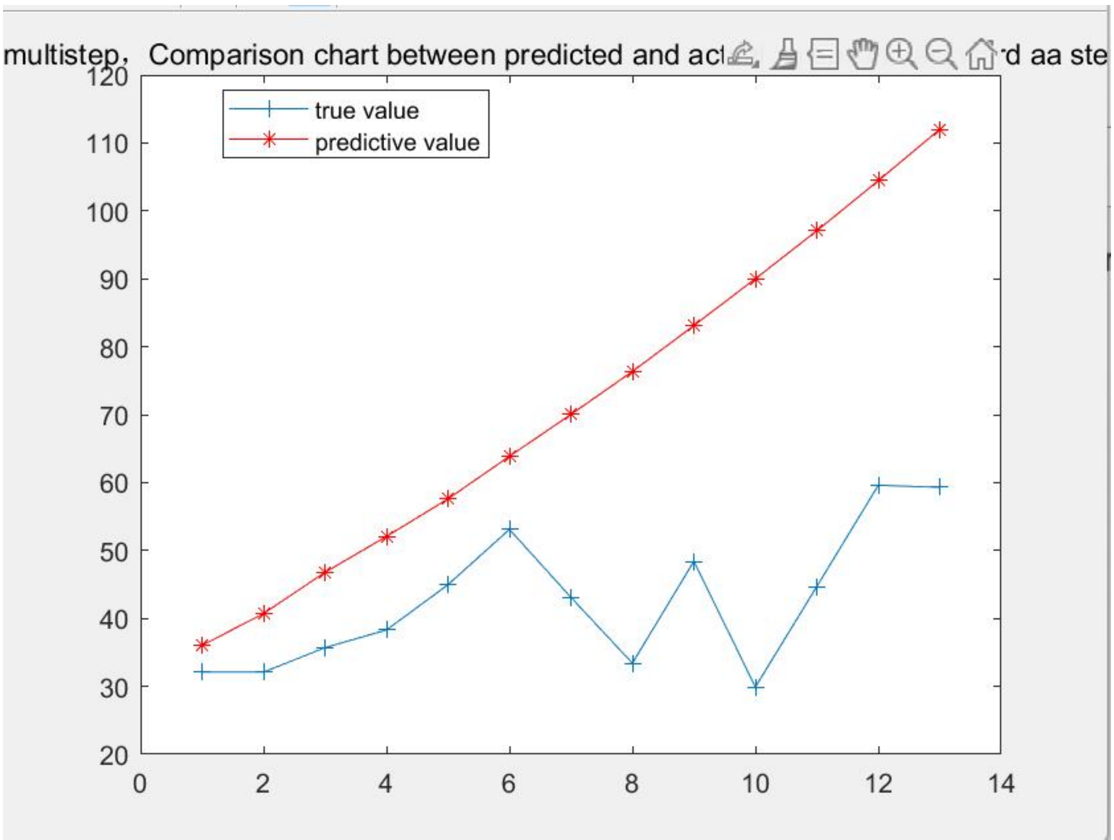
4.2.3model diagnosis

Diagnose the estimated ARIMA model and check if the residual of the model conforms to the white noise assumption. We use absolute error and relative error to test the model, and the following figure shows the comparison between predicted values and actual values. (Divided into single step and multi-step)

Figure 13 AR(q)Model sample approximation prediction curve



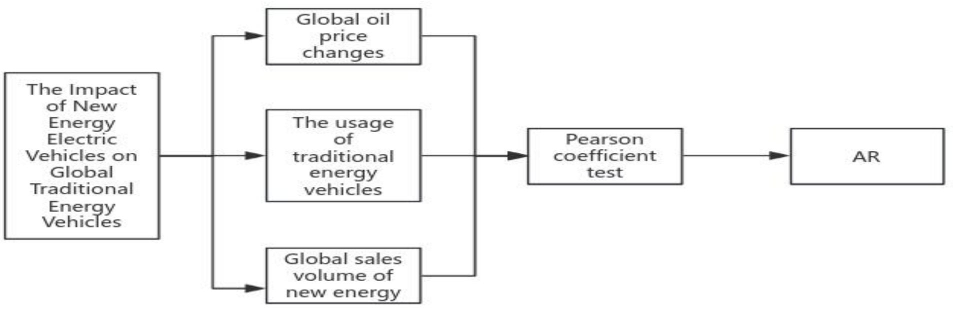

single step，Comparison between predicted and actu
ackward
true value
predictive value


multistep，Comparison chart between predicted and ac
d aa ste
true value
predictive value

4.3 Solving problem three

Study the impact of new energy electric vehicles on the global traditional energy vehicle industry. Extract three related factors: global oil price changes (indirectly reflecting the global use of traditional energy vehicles), research and development of traditional energy technologies, and global sales of new energy vehicles. Perform Pearson correlation coefficient test first, then further conduct causal test, and finally establish AR[3]

Figure 14 AR chart



4.3.1Calculate the Pearson correlation coefficient

The table of the data used is as follows：

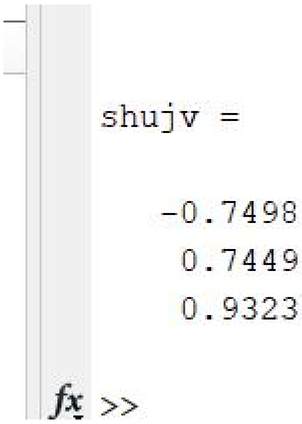
Figure 15 Related data used

Global oil price sales volume (Yuan)	Global sales volume of new energy vehicles (10000 units)	Research and development volume of traditional energy technologies (in billions)
56.99	120.6	131.3
54.25684211	122.4315789	132.5
51.52368421	124.2631579	133.7
48.79052632	126.0947368	134.9
46.05736842	127.9263158	136.1
43.32421053	129.7578947	137.3
40.59105263	131.5894737	138.5

41.53157895	155.2	139.7526316
44.30894737	189.7	141.0315789
47.08631579	224.2	142.3105263
49.86368421	258.7	143.5894737
52.64105263	293.2	144.8684211
55.41842105	327.7	146.1473684
58.30842105	352.5105263	147.4578947
61.42368421	357.9421053	148.8315789
64.53894737	363.3736842	150.2052632
67.65421053	368.8052632	151.5789474
70.76947368	374.2368421	152.9526316
73.88473684	379.6684211	154.3263158
77	385.1	155.7

The Pearson correlation coefficient is as follows:

Figure 16 correlation coefficient



According to the results, the Pearson correlation coefficient test was conducted The quotient of covariance and standard deviation between two variables:

$$\rho_{X,Y} = \frac{\operatorname{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[(X-\mu_X)(Y-\mu_Y)]}{\sigma_X \sigma_Y} \tag{4}$$

Represented by lowercase English letters:

$$r = \frac{\sum_{i=1}^{n} (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n} (X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}}. \tag{5}$$

$$r = \frac{1}{n-1}\sum_{i=1}^{n} \left(\frac{X_i - \bar{X}}{\sigma_X}\right)\left(\frac{Y_i - \bar{Y}}{\sigma_Y}\right) \tag{6}$$

The above is to solve the correlation coefficient

Conclusion: By solving the correlation coefficients of the three factors, it can be seen that new energy electric vehicles will have a certain impact on the global traditional energy vehicle industry. However, there will still be a positive correlation between global oil prices, research and development of traditional energy technologies, and other factors.

The above is to solve the correlation coefficient

Conclusion: By solving the correlation coefficients of the three factors, it can be seen that new energy electric vehicles will have a certain impact on the global traditional energy vehicle industry. However, there will still be a positive correlation between global oil prices, research and development of traditional energy technologies, and other factors.

4.3.2 Perform a causal test on the above

Further use causal testing to screen for factors that are more relevant to the impact of the global traditional energy vehicle industry. For multivariate time series, if input sequences that have a significant impact on the response variable can be found and their cointegration relationship can be verified, it is very useful for accurately predicting the fluctuations of the response variable, or indirectly controlling the development of the response variable by controlling the value of the input sequence. But the premise is that there is a true causal relationship between the input sequence and the response sequence[4], and it must be the input sequence as the cause and the response sequence as the result. Therefore, the factors that truly affect the global traditional automotive industry can be obtained.

The causal test is as follows：

Figure 17 Causal test

Further use causal testing to screen for factors that are more relevant to the impact of the global traditional energy vehicle industry. For multivariate time series, if input sequences that have a significant impact on the response variable can be found and their cointegration relationship can be verified, it is very useful for accurately predicting the fluctuations of the response variable, or indirectly controlling the development of the response variable by controlling the value of the input sequence. But the premise is that there is a true causal relationship between the input sequence and the response sequence, and it must be the input sequence as the cause and the response sequence as the result. Therefore, the factors that truly affect the global traditional automotive industry can be obtained.

4.3.3 Establishing a vector autoregressive model

The basic form of a vector autoregressive model is the autoregressive expression of a weakly stationary process, which describes several variables within the same sample period that can serve as linear functions of their past values:

$$Y_t = \Phi_0 + \Phi_1 Y_{t-1} + \cdots + \Phi_p Y_{t-p} + BX_t + \varepsilon_t, t = 1,2,\cdots,T \tag{7}$$

Wherein:

$$Y_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{kt} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{kt} \end{pmatrix}, \Phi_0 = \begin{pmatrix} \phi_{10} \\ \phi_{20} \\ \vdots \\ \phi_{k0} \end{pmatrix} \tag{8}$$

$$\Phi_i = \begin{pmatrix} \phi_{11}(i) & \phi_{12}(i) & \cdots & \phi_{1k}(i) \\ \phi_{21}(i) & \phi_{22}(i) & \cdots & \phi_{2k}(i) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_{k1}(i) & \phi_{k2}(i) & \cdots & \phi_{kk}(i) \end{pmatrix}, i = 1,2,\cdots,p$$

$$Y(t) = A(1)Y(t-1) + \cdots + A(n)Y(t-n) + BX(t) + e(t) \tag{9}$$

$Y(t)$ is the global sales volume of traditional energy vehicles

$X(t)$ is a relatively relevant factor obtained earlier

$A(1)\cdots A(n)$ and B is an estimated coefficient matrix,

$e(t)$ is an error vector. The error variables within the error vector are allowed to be correlated, but these error variables are autocorrelated and not correlated with$Y(t), Y(t-1), Y(t-2), Y(t-3), \cdots Y(t-n)$ and $X(t)$

Within VAR, the best estimate for each equation is the ordinary least squares estimate.

The following linear function can be obtained from the results of Matlab

The following linear function can be obtained from the results of Matlab：

$$y1=-3.1011y2+0.0002y3+0.0061y4+0.0173 \tag{10}$$

4.4 Solving problem four

Regarding question four, the title requires us to analyze the relevant policies released by foreign countries for the development of new energy vehicles in China, and analyze the impact of these policies on the development of new energy vehicles in China. To address this issue, we have decided to use foreign data on the development of new energy vehicles in China before the policy release, and then use this data to predict the data for the next few years, Next, we will collect data on the development of new energy vehicles after targeted foreign policies have been released. Finally, we will compare the predicted data with the actual data we have collected and analyze the impact of targeted foreign policies on the development of new energy vehicles in China.

Related policy collection:

The United States passed the Inflation Reduction Act in August 2022, which includes $369 billion in energy security and climate change investments. The most prominent support for the electric vehicle and battery industry is the consumption tax credit for each electric vehicle sold, as well as the advanced manufacturing industry credit for battery and module production.

Firstly, in terms of consumption tax credit, a tax credit of $7500 will be provided for the sales of new electric vehicles. However, the Inflation Reduction Act stipulates that the final assembly location of vehicles must be in the United States, and eligibility is limited by the specific price cap of the vehicle and the family/individual income cap. The credit is divided into two parts and must meet 1) battery component requirements ($3750 per vehicle) and 2) critical mineral requirements ($3750 per vehicle). The Inflation Reduction Act also stipulates that consumers who purchase any used electric vehicle for at least two years can receive a tax credit of $4000 or 30% of the car's price, whichever is lower. Similarly, specific price and revenue limits must be met. Finally, the additional clause excludes electric vehicles involving "foreign entities of concern". [1]

On October 4, 2023, when Chinese new energy vehicle enterprises are still busy in the promotion of the National Day Golden Week, the European Commission officially announced that it decided to launch a countervailing investigation on new energy electric vehicles from China, which shows that on September 13, the official declaration of "double anti" investigation on Chinese new energy vehicles by von der Leyen, the chairman of the European Commission, was officially launched. [2]

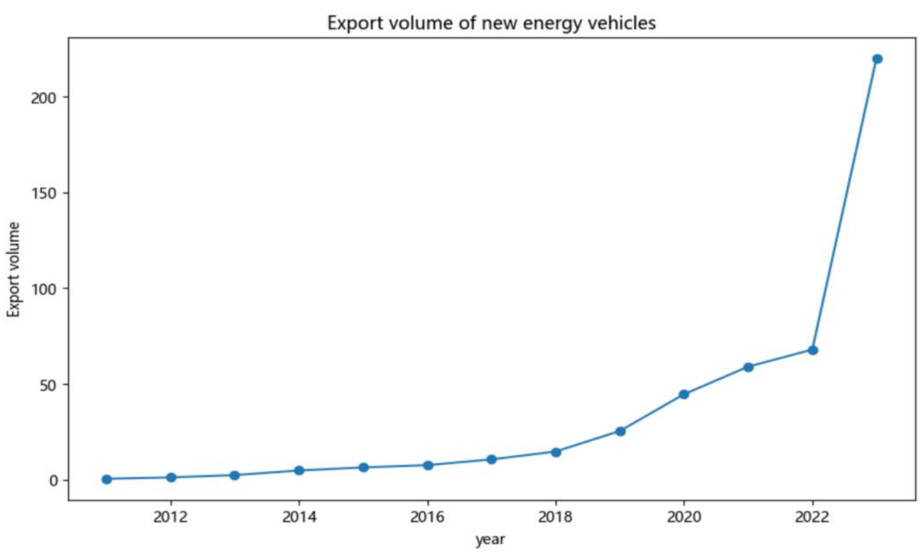
The following is the data we have collected:

Figure 18Export volume of new energy vehicles (10000 units)

Year	Export volume of new energy vehicles (10000 units)
2011	0.5
2012	1.2
2013	2.4
2014	4.8
2015	6.4
2016	7.6
2017	10.6
2018	14.7
2019	25.4
2020	44.6
2021	59
2022	67.9
2023	220

Visualize the data as shown in the figure below:

Figure 19 Export volume of new energy vehicles



We analyzed the above data and found that it has a small amount of data and a short prediction period. Therefore, we decided to use the grey prediction method to process the original data, convert it into a grey sequence, and establish a differential equation model for solution.

Firstly, perform a rank comparison test, assuming that the original sequence is:

$$x^{(0)}=(x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \tag{11}$$

By calculating the following equation:

$$\lambda(k)=\frac{x^{(0)}(k-1)}{x^{(0)}(k)} \tag{12}$$

Meet with:

$$\lambda(k) \in \left(e^{-\frac{2}{n+1}}, e^{\frac{2}{n+2}}\right) \tag{13}$$

Thus established

GM（1，1）model, and make gray predictions. The original sequence is first generated after an accumulation process

$x^{(0)}$ of 1-AGO rank:

$$x^{(1)}=(x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)) \tag{14}$$

There into:

$$x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i) \quad k=1,2,3,\ldots\ldots,n \tag{15}$$

Establish the first-order differential linear equations, i.e., the Gray Differential Equations, and obtain

GM（1，1）the mean form of the model:

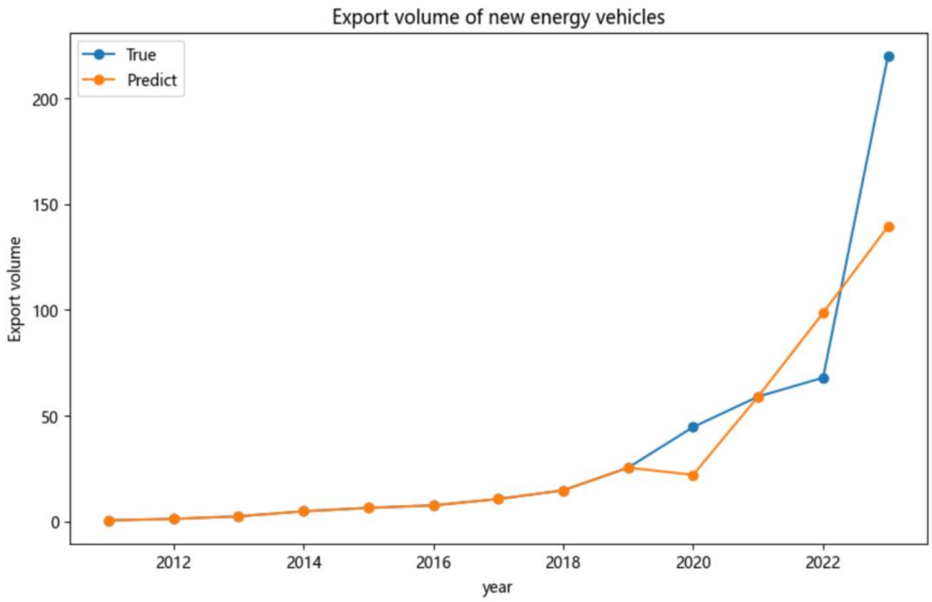
$$x^{(0)}(k)+az^{-1}(k)=b \tag{16}$$

ByGM（1，1）the corresponding whitening differential equation of the model:

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{17}$$

Then, the prediction value of the model is obtained by solving a and b by the least squares method, and the predicted value of new energy vehicle sales in 2022 and 2023 is 99 and 139, respectively：

Figure20 Export volume of new energy vehicle



By carefully observing the above charts, we can find that the development of China's new energy vehicles has been more or less affected after the introduction of relevant policies in the United States, but in 2020, the development of China's new energy vehicles is still developing rapidly, which is enough to see that the rapid development of new energy in China has become an inevitable trend

4.5 Solving problem five

4.5.1 Analysis of the train of thought for question five

Question 5 requires us to analyze the impact of electrification of urban new energy electric vehicles on the ecological environment. And provide the calculation results for a city population of 100000.

Because it involves calculations, specific calculation results are definitely required in the end. The main indicators for considering the impact of ecological environment here are carbon emissions, comprehensive energy consumption, etc.[5]

So we can consider finding the total number of various types of cars in the country, reducing the number of cars to 100000 people based on the population ratio, and calculating the current energy consumption and carbon emissions. Then it is electrified, and the energy consumption and carbon emissions after electrification are calculated to obtain the emission reduction effect of new energy electrification.

4.5.2 Data collection

This article collects the national motor vehicle ownership as shown in the table below:

Figure 21 National motor vehicle ownership

National population	1411.75 million people
Traditional new energy vehicles	311.79 million vehicles
New energy vehicles	16.21 million vehicles

According to the proportion, it is estimated that the number of various types of cars in a city with a population of 100000 is shown in the table below:

Figure 22 100wPopulation and motor vehicle ownership

National population	100million people
Traditional new energy vehicles	22 million vehicles
New energy vehicles	1.3 million vehicles

4.5.3 Energy Consumption Calculation

Assuming a car has a full cycle carbon emissions of 240000 kilometers driven for 16 years, it can be inferred that pure electric vehicles have a full cycle carbon emissions.carbon emissions are 39 tCO2e, hybrid vehicles have a full life cycle carbon emissions of 47 tCO2e, and fuel vehicles have a full life cycle carbon emissions of 55 tCO2e.

Using this indicator, calculate the carbon emissions before and after electrification of a traditional energy city with a population of 100000. The resulting indicators are shown in the table below:

Figure 23 100wComparison of carbon emissions before and after population urbanization(t)

Type	Before electrification	After electrification	Decline ratio
Tradition Energy	12100000	8580000	29.1%
Pure electric	390000	390000	0.0%
Hybrid vehicles	141000	117000	17.0%
Amount	12631000	9087000	28.1%

The comparative analysis of carbon emissions before and after population urbanization shows that carbon emissions have significantly decreased after urbanization, with an overall decrease of 28%

4.6 Solving problem six

Dear citizens：

Theme: Driving the Future, Let Green Power Illuminate Our City!

At this moment full of passion and innovation, we stand on the shoulders of giants of history, gazing at the future full of infinite possibilities. New energy electric vehicles are leading us towards a greener and smarter future with their unique charm. At this critical moment, new energy electric vehicles have become an important tool for us to change.

The benefits of new energy electric vehicles are obvious:

1.Reducing carbon emissions: Scientific data shows that electric vehicles can reduce carbon emissions by about 30% compared to traditional fuel vehicles, which is of great significance for curbing global warming and climate change.

2.Improving air quality: The operation of electric vehicles does not produce exhaust, which will greatly improve urban air quality and make our breathing healthier.

3.Improving energy efficiency: The energy conversion efficiency of electric motors far exceeds that of internal combustion engines, making the operation of electric vehicles more efficient and energy-saving.

4.Reducing resource dependence: Promoting electric vehicles will reduce our dependence on nonrenewable resources, promote the transformation of energy structure, and move towards a more sustainable development path.

The global influence of electric vehicles:

1.Economic growth: The electric vehicle industry has created millions of job opportunities globally, forming a complete industrial chain covering research and development, manufacturing, sales, and services, becoming a new point of economic growth.

2.Technological innovation: The development of electric vehicles has driven continuous innovation in related technologies, including battery technology, charging facility construction, and intelligent transportation systems.

3.Energy transformation: With the popularization of electric vehicles, the demand for clean energy continues to increase, which in turn promotes the development and utilization of renewable energy such as solar and wind energy.

Imagine our city, with zero emission electric cars shuttling through the streets. They are silent yet possess endless power. They are no longer moving sources of pollution, but have become the respiratory organs of cities, bringing us fresh air and showcasing a true green travel style.

The emergence of electric vehicles is like a dawn, illuminating our path forward.

It not only reduces carbon emissions, but also changes our dependence on energy. Without the roar of gasoline powered cars, our city has become more peaceful and harmonious. And the problems that once troubled us, such as air pollution and noise pollution, are gradually becoming a thing of the past.

What is even more exciting is that new energy electric vehicles are not only a revolution in transportation, but also an innovation in lifestyle. Through charging stations, we can easily charge our beloved cars and achieve true green travel. At the same time, the development of electric vehicles has also driven innovation in battery technology, construction of charging infrastructure, and popularization of intelligent transportation, creating a more convenient, efficient, and environmentally friendly future travel ecosystem for us.

Friends, standing at the forefront of this era, we cannot stand idly by. Let's embrace the beautiful era of new energy electric vehicles! Let us shoulder the responsibility of environmental protection together and contribute our efforts to the beautiful future of our planet!

Choosing new energy electric vehicles means choosing a greener and better future. Let's ride the future together and let green energy illuminate our city!

Thank you for your attention and support!

Yours sincerely!

Salute!

五、References

The first question is about the code:

```
import matplotlib.pyplot as plt

years = [2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022]
sales = [1.8, 7.5, 33.1, 50.7, 77.7, 125.6, 120.6, 136.7, 352.1, 688.7]

plt.figure(figsize=(10, 6))

bars = plt.bar(years, sales, alpha=0.5)

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 1), va='bottom')

plt.plot(years, sales, marker='o', color='r')

plt.title('Sales of new erenge vehicles ')
plt.xlabel('year')
plt.ylabel('salas')


plt.grid(True)


plt.show()
```

```python
from statsmodels.formula.api import ols
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

energe=pd.read_csv('F:/newenerge.csv',encoding='UTF-8')
model=ols("y~x1+x2+x3+x4+x5",data=energe).fit()
print(model.summary())
```

```python
from statsmodels.stats.anova import anova_lm
anova_lm(model,typ=1)
```

```python
from statsmodels.formula.api import ols
import pandas as pd

energy = pd.read_csv('F:/newenerge.csv',encoding='UTF-8')
model = ols("y ~ x1 + x2 + x3 + x4 + x5", data=energy).fit()

# 打印回归系数
print("回归系数：")
print(model.params)
```

The second question is about the code:

```matlab
clear; clc


DD=readmatrix("现有数据.xlsx");

P=DD(1:35,2)';

N=length(P);

n=20;

F = P(1:n+2);


Yt=[0,diff(P,1)];

L=diff(P,2);

Y=L(1:n);

a=length(L)-length(Y);

aa=a;


Ux=sum(Y)/n ;
```

```
yt=Y-Ux;
b=0;
for i=1:n
b=yt(i)^2/n+b;
end
v=sqrt(b);
Y=zscore(Y);
f=F(1:n);
t=1:n;

R0=0;
for i=1:n
R0=Y(i)^2/n+R0;
end
for k=1:20
R(k)=0;
for i=k+1:n
R(k)=Y(i)*Y(i-k)/n+R(k);
end
end
x=R/R0 ;

X1=x(1);xx(1,1)=1;X(1,1)=x(1);B(1,1)=x(1);
K=0;T=X1;
for t=2:n
at=Y(t)-T(1)*Y(t-1);
K=(at)^2+K;
end
U(1)=K/(n-1) ; for i =1:19
B(i+1,1)=x(i+1);
xx(1,i+1)=x(i);
A=toeplitz(xx);
XX=A\B;
XXX=XX(i+1);
X(1,i+1)=XXX;
```

```
K=0;T=XX;
for t=i+2:n
r=0;
for j=1:i+1
r=T(j)*Y(t-j)+r;
end
at= Y(t)-r;
K=(at)^2+K;
end
U(i+1)=K/(n-i+1);
end

q=2;
S(1,1)=R0;
for i = 1:q-1
S(1,i+1)=R(i);
end
G=toeplitz(S);
W=inv(G)*[R(1:q)]' ;
U=20*U ;
for i=1:20
AIC2(i)=n*log(U(i))+2*(i) ;
end

q=2;
C=0;K=0;
for t=q+2:n
at=Y(t)+Y(q+1);
for i=1:q
at=-W(i)*Y(t-i)-W(i)*Y(q-i+1)+at;
end
at1=Y(t-1);
for i=1:q
at1=-W(i)*Y(t-i-1)+at1;
end
```

```
C=at*at1+C;
K=(at)^2+K;
end
p=C/K ;

XT=[L(n-q+1:n+a)];
for t=q+1:q+a
m(t)=0;
for i=1:q
m(t)=W(i)*XT(t-i)+m(t);
end
end
m=m(q+1:q+a);

for i =1:a
m(i)=Yt(n+i+1)+m(i);
z1(i)=P(n+i+1)+m(i);
end
z1

for t=q+1:n
r=0;
for i=1:q
r=W(i)*Y(t-i)+r;
end
at= Y(t)-r;
end
figure;
for t=q+1:n
y(t)=0;
for i=1:q
y(t)=W(i)*Y(t-i)+y(t);
end
y(t)=y(t)+at;
```

```
y(t)=Yt(t+1)-y(t);
y(t)=P(t+1)-y(t);
end
plot(y,'r.');
hold on;
plot(n+2:n+a+1,z1,'r-*');
hold on;
plot(P,"--");
title('AR(q)模型样本逼近预测曲线');
legend("训练样本预测值","测试集预测值","真实值与预设值","Location","best");

D_a=P(n+2:end-1);
for i=1:a
e6_a(i)=D_a(i)-z1(i);
PE6_a(i)= (e6_a(i)/D_a(i))*100;
end
e6_a;
PE6_a; 1-abs(PE6_a);

mae6_a=sum(abs(e6_a)) /10 ;

MAPE6_a=sum(abs(PE6_a))/10

figure;
plot(1:a,D_a,'-+')
hold on;
plot(z1,'r-*');
title('单步，向后 a 步预测值和实际值对比图');
legend("真实值","预测值","Location","best");
hold off;

Z(1)=0;Xt=0;
for i =1:q
Xt(1,i)=Y(n-q+i);
end
```

```
for i =1:q
Z(1)=W(i)*Xt(q-i+1)+Z(1);
end

for l=2:q
K(l)=0;
for i=1:l-1
K(l)=W(i)*Z(l-i)+K(l);
end
G(l)=0;
for j=l:q
G(l)=W(j)*Xt(q+l-j)+G(l);
end
Z(l)=K(l)+G(l);
end
for l=q+1:aa
K(l)=0;
for i=1:q
K(l)=W(i)*Z(l-i)+K(l);
end
Z(l)=K(l);
end

r=Z*v+Ux ;
r(1)=Yt(n+2)+r(1);
z(1)=P(n+2)+r(1) ;
for i=2:aa
r(i)=r(i-1)+r(i);
z(i)=z(i-1)+r(i) ;
end

D=P(n+2:end-1);
for i=1:aa
e6(i)=D(i)-z(i);
```

```
PE6(i)= (e6(i)/D(i))*100;
end
e6 ;
PE6 ;
1-abs(PE6) ;

mae6=sum(abs(e6)) /10 ;

MAPE6=sum(abs(PE6))/10 ;

figure;
plot(1:aa,D,'-+')
hold on;
plot(z,'r-*');
title('多步，向后 aa 步预测值和实际值对比图');
legend("真实值","预测值","Location","best");
hold off;
```

The third question is about the code:

huigui.m *

```
clc
clear all;
y1 = [120.6; 132.2; 350.7; 385.1];
y2 = [2454.8,2394.5,2274.1,1299.9];
y3 = [56.99,39.68,57.27,77];
y4 = [131.3,138.9,147,155.7];

X = [y2; y3; y4]';
X = [ones(size(X, 1), 1) X];
coeffs = regress(y1, X);

p = size(X, 2) / size(X, 1);
A = reshape(coeffs(1:end), [], p)';
disp(A)

```

```matlab
function coeff = myPearson(X , Y)


if length(X) ~= length(Y)
    error('两个数值数列的维数不相等');
    return;
end

fenzi = sum(X .* Y) - (sum(X) * sum(Y)) / length(X);
fenmu = sqrt((sum(X .^2) - sum(X)^2 / length(X)) * (sum(Y .^2) - sum(Y)^2 / length(X)));
coeff = fenzi / fenmu;

end %函数myPearson结束
```

```matlab
y1 = [120.6, 132.2, 350.7, 385.1];
y2 = [2454.8,2394.5,2274.1,1299.9];
data = [y1', y2'];

sigma = cov(data);

mu_y1 = mean(y1);
mu_y2 = mean(y2);

p = 1;

F = zeros(p, p);
f = zeros(p, 1);

for k = 1:p
    for j = 1:p
        if k > j
            continue;
        else
            F(k, j) = sigma(1, 1) / sigma(1, 1+j-k);
            f(k) = f(k) + F(k, j);
        end
    end
end

disp(['f = ', num2str(f)]);
if f > 1
    disp('y2 granger causes y1');
else
    disp('y1 granger causes y2');
end

```

```
x = [2019, 2020, 2021, 2022];
y4 = [120.6; 132.2; 350.7; 385.1];
n = 20;
xi = linspace(2019, 2022, n);

y44 = interp1(x, y4, xi)';
```

```
clc,clear;
y1 = readmatrix('全球新能源汽车销售量.xlsx');
y2 = readmatrix('全球油价销售量.xlsx');
data = [y1', y2'];

sigma = cov(data);

mu_y1 = mean(y1);
mu_y2 = mean(y2);

p = 1;

F = zeros(p, p);
f = zeros(p, 1);

for k = 1:p
    for j = 1:p
        if k > j
            continue;
        else
            F(k, j) = sigma(1, 1) / sigma(1, 1+j-k);
            f(k) = f(k) + F(k, j);
        end
    end
end

disp(['f = ', num2str(f)]);
if f > 1
    disp('y2 granger causes y1');
else
    disp('y1 granger causes y2');
end
```

huigui.m myPearson.m untitled5.m w.m

```
clc
clear all
data=readmatrix('数据.xlsx');
shujv=[];
for i=2:size(data,2)
    tmp=myPearson(data(:,1),data(:,i));
    shujv=[shujv;tmp]
end
```

```
import matplotlib.pyplot as plt

years = [2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022]
sales = [1.8, 7.5, 33.1, 50.7, 77.7, 125.6, 120.6, 136.7, 352.1, 688.7]

plt.figure(figsize=(10, 6))

bars = plt.bar(years, sales, alpha=0.5)

for bar in bars:
    yval = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2, yval, round(yval, 1), va='bottom')

plt.plot(years, sales, marker='o', color='r')

plt.title('Sales of new erenge vehicles ')
plt.xlabel('year')
plt.ylabel('salas')


plt.grid(True)


plt.show()
```

```
from statsmodels.formula.api import ols
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression

energe=pd.read_csv('F:/newenerge.csv',encoding='UTF-8')
model=ols("y~x1+x2+x3+x4+x5",data=energe).fit()
print(model.summary())
```

```
from statsmodels.stats.anova import anova_lm
anova_lm(model,typ=1)
```

```python
from statsmodels.formula.api import ols
import pandas as pd

energy = pd.read_csv('F:/newenerge.csv',encoding='UTF-8')
model = ols("y ~ x1 + x2 + x3 + x4 + x5", data=energy).fit()

# 打印回归系数
print("回归系数: ")
print(model.params)
```

```python
import numpy as np

# 数据
years = np.array([2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021])
exports = np.array([0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 44.9, 59])

# 累加生成
def accumulate(data):
    s = np.zeros(data.shape)
    for i in range(data.shape[0]):
        s[i] = np.sum(data[0:i+1])
    return s

# 灰色预测模型
def grey_model(x0):
    x1 = accumulate(x0)
    z1 = (x1[:-1] + x1[1:]) / 2.0
    B = np.array([-z1, np.ones(z1.shape)]).T
    Yn = x0[1:].reshape((x0.shape[0]-1, 1))
    [[a], [b]] = np.dot(np.dot(np.linalg.inv(np.dot(B.T, B)), B.T), Yn)
    f = np.zeros(x0.shape[0])
    f[0] = x0[0]
    for i in range(1, f.shape[0]):
        f[i] = (1 - a) * (x0[0] if i == 1 else f[i-1]) + b
    return f, a, b

# 预测
def predict(data, a, b, n):
    f = np.zeros(n)
    f[0] = data[0]
    for i in range(1, n):
        f[i] = (1 - a) * (data[0] if i == 1 else f[i-1]) + b
    return f

# 计算预测值
f, a, b = grey_model(exports)
print('预测值: ', f)

# 预测2022和2023年的数据
n = 2  # 预测未来2年的数据
f = predict(exports, a, b, years.shape[0] + n)
print('2022年预测值: ', f[-2])
print('2023年预测值: ', f[-1])
```

```
import matplotlib.pyplot as plt

# 数据
years = [2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023]
exports = [0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 44.6, 59, 67.9, 220]

# 预测值
pred_exports = [0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 22, 59, 98.5, 139.4]  # 这里应替换为你的预测值

# 创建图形
plt.figure(figsize=(10, 6))

# 绘制实际值折线图
plt.plot(years, exports, marker='o', label='True')

# 绘制预测值折线图
plt.plot(years, pred_exports, marker='o', label='Predict')

# 设置标题和标签
plt.title('Export volume of new energy vehicles')
plt.xlabel('year')
plt.ylabel('Export volume')

# 显示图例
plt.legend()

# 显示图形
plt.show()
```

The forth question is about the code:

```
import matplotlib.pyplot as plt
plt.rcParams['font.sans-serif'] = ['Microsoft YaHei'] # 在设置中文字体，否则中文无法正常显示
plt.rcParams['axes.unicode_minus'] = False # 用来正常显示负号

# 数据
years = [2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023]
exports = [0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 44.6, 59, 67.9, 220]

# 创建图形
plt.figure(figsize=(10, 6))

# 绘制折线图
plt.plot(years, exports, marker='o')

# 设置标题和标签
plt.title('Export volume of new energy vehicles')
plt.xlabel('year')
plt.ylabel('Export volume')

# 显示图形
plt.show()
```

```
import matplotlib.pyplot as plt

# 数据
years = [2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023]
exports = [0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 44.6, 59, 67.9, 220]

# 预测值
pred_exports = [0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 22, 59, 98.5, 139.4]  # 这里应替换为你的预测值

# 创建图形
plt.figure(figsize=(10, 6))

# 绘制实际值折线图
plt.plot(years, exports, marker='o', label='True')

# 绘制预测值折线图
plt.plot(years, pred_exports, marker='o', label='Predict')

# 设置标题和标签
plt.title('Export volume of new energy vehicles')
plt.xlabel('year')
plt.ylabel('Export volume')

# 显示图例
plt.legend()

# 显示图形
plt.show()
```

```
import numpy as np

# 数据
years = np.array([2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021])
exports = np.array([0.5, 1.2, 2.4, 4.8, 6.4, 7.6, 10.6, 14.7, 25.4, 44.9, 59])

# 累加生成
def accumulate(data):
    s = np.zeros(data.shape)
    for i in range(data.shape[0]):
        s[i] = np.sum(data[0:i+1])
    return s

# 灰色预测模型
def grey_model(x0):
    x1 = accumulate(x0)
    z1 = (x1[:-1] + x1[1:]) / 2.0
    B = np.array([-z1, np.ones(z1.shape)]).T
    Yn = x0[1:].reshape((x0.shape[0]-1, 1))
    [[a], [b]] = np.dot(np.dot(np.linalg.inv(np.dot(B.T, B)), B.T), Yn)
    f = np.zeros(x0.shape[0])
    f[0] = x0[0]
    for i in range(1, f.shape[0]):
        f[i] = (1 - a) * (x0[0] if i == 1 else f[i-1]) + b
    return f, a, b

# 预测
def predict(data, a, b, n):
    f = np.zeros(n)
    f[0] = data[0]
    for i in range(1, n):
        f[i] = (1 - a) * (data[0] if i == 1 else f[i-1]) + b
    return f

# 计算预测值
f, a, b = grey_model(exports)
print('预测值: ', f)

# 预测2022和2023年的数据
n = 2  # 预测未来2年的数据
f = predict(exports, a, b, years.shape[0] + n)
print('2022年预测值: ', f[-2])
print('2023年预测值: ', f[-1])
```

六、Appendix

[1] 高雅.通胀削减法案生效后美国新能源汽车销量显著改善[N].第一财经日报,2023-03-21(A05).DOI:10.28207/n.cnki.ndycj.2023.001233

[2] 青木;任重.中国车企回应欧盟反补贴调查[N].环球时报,2023-10-27(011).DOI:10.28378/n.cnki.nhqsb.2023.007684

[3]何力武.国外新能源汽车发展现状与产业扶持政策[J].绿叶,2012,(03):39-44.

[4] 张芳.中国绿色产业发展的路径选择与制度创新研究[D].吉林大学,2020.DOI:10.27162/d.cnki.gjlin.2020.007181

[5] 张海斌.基于情景构建的新能源汽车产业市场演化及引导研究[D].南京大学,2016.DOI:10.27235/d.cnki.gnjiu.2016.000