Team Number :	apmcm2305738
Problem Chosen :	C

2023 APMCM summary sheet

Abstract

The "New Energy Electric Vehicles" (NEEVs) is a rapidly developing field. Advances in technology, increasing environmental awareness, and a global shift towards sustainable transportation have propelled the growth and innovation within the NEEVs sector. This article uses GRA model, ARIMA model, Linear Regression model, together with Green Vehicle Popularization and Environmental Impact model to study the development trend of NEEVs in China.

Question 1 involves objectively evaluating factors influencing NEEVs development. Indicators and data are collected, normalized to eliminate fluctuations, and Grey Relational Analysis is applied to assess the relevance of each factor. The goal is to determine the strength of each factor's impact on NEEV development.

Question 2 focuses on studying industry development data on China's NEEVs and forecasting trends for the next 10 years. Key indicators reflecting industry development are identified, and an ARIMA model, suitable for time series data, is proposed. The results are graphed to illustrate development patterns over time.

To solve question 3, data influencing NEEV development and global traditional vehicle sales figures are collected. A Linear Regression model is chosen to predict global conventional vehicle sales based on NEEV development indicators, with results validated against existing global traditional vehicle development data.

In response to question 4, utilizes the Linear Regression model to examines the impact of resistance policies on NEEV development in China. NEEV sales, without considering the resistance policy, serve as an output representation. The resistance policy indicator is then incorporated into the model, and the trend in sales is observed to assess the policy's effects on NEEV development.

For question 5, indicators impacting both the ecological environment and NEEVs are identified. Through GVPEI model, interactions between these indicators are studied, incorporating population as a parameter. We aimed to predict the impact of NEEV electrification on the city's ecology, considering a population of one million as the output result.

Finally, we wrote an open letter to emphasise the impact of new energy electric vehicle on the environment

Keywords: New Energy Electric Vehicles, GRA, ARIMA, Linear Regression

Contents

1 Introduction

1.1 Background

China has been actively promoting the development and adoption of new energy electrical vehicles (NEEVs) as part of its efforts to address environmental concerns, reduce reliance on fossil fuels, and promote sustainable transportation. Throughout the year, the Chinese government has implemented various policies and incentives and invested heavily in charging infrastructure in urban areas to stimulate and support the growth of the new energy vehicle market. The increase in consumer awareness and acceptance of NEEVs, coupled with government's icentive and a growing understanding of the environmental benefits of new energy vehicles, have contributed to a rising demand for NEEVs among Chinese consumer. At the end, in results of Chinese government promotion of NEEVs, China had reduced its air pollution and greenhouse gas emmisions and become the world's largest market for NEEVs. Nevertheless, it is important to note that the landscape of NEEVs in China is dynamic, with ongoing developments in policies, technologies and market trends shaping the industry's future. Therefore, we can build models based on the historical data in economic conditions, market performance, government policies, infrastructure development and technology innovation and reflect the development trends of NEEVs in China.

1.2 Problem requirements

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

2 Problem analysis

2.1 Analysis of Problem One

In order to analyze the main factors that affect the development of new energy electric vehicles in China, we can objectively assign an evaluation score to the possible factors influencing NEEVs development for comparison. After collecting relevant indicators and data, we can use normalization method to eliminate potential data fluctuations. Then, we use Grey Relational Analysis to evaluate the degree of relevance of each indicators, and finally determine the strength of the impact of a particular factors on the NEEVs development in China.

2.2 Analysis of Problem Two

Problem two requires us to study the patterns inherent in the industry development data on China's NEEVs and forecast the development trend in the next 10 years. To achieve this, we need to find a set of indicators that are able to reflect the develepment in this industry and establish a time series forecasting model that fits the characteristics of the data. In this case, the ARIMA model is particularly well-suited for time series data, where observations are recorded over time. This aligns with the nature of data related to the development of NEEVs, which involves historical trends and patterns. The result has to be graphed to depicts the development patterns.

2.3 Analysis of Problem Three

In order to determine the impact of new energy electric vehicles (NEEVs) on the global traditional energy vehicle industry, we can collect data that influences the development of NEEVs, as well as data that best reflects the global development of traditional vehicles, namely sales figures. Propose a mathematical model for predicting global conventional vehicle sales based on indicators influencing NEEV development, and evaluate the reliability of the forecast results by comparing them with existing global traditional vehicle development data. In this case, as we need to predict trends by studying the relationships between indicators, we have chosen a Linear Regression model as the mathematical model.

2.4 Analysis of Problem Four

Aiming at problem four, we utilize the same model as in problem three, namely the Linear Regression model, to analyze the impact of the resistance policy on the development of New Energy Electric Vehicles (NEEVs) in China. Through the study of the relationships between the chosen indicators, we take the NEEV sales without considering the resistance policy indicator as an output representation of development. We then incorporate the resistance policy indicator as one of the variables in the model, outputting the trend in sales. Ultimately, we observe the development trend of NEEV sales and assess the effects of the resistance policy on the development of NEEVs based on the presence of the resistance policy indicator in this trend.

2.5 Analysis of Problem Five

To address this issue, we first need to identify indicators that simultaneously impact both the ecological environment and NEEVs. By analyzing these indicators and studying how they interact with each other, discovering patterns, and then introducing population as a parameter, we can predict the impact of NEEV electrification on the city's ecology. This involves using data analysis to understand the interplay of these indicators, incorporating population as a parameter, and forecasting the developmental trends of indicators when the population is one million as the output results.

2.6 Analysis of Problem Six

Based on the conclusion of Problem Five, we can write an open letter about the environmental awareness, contributions of NEEVs and the benefits to popularize NEEVs.

3 Symbol description

Tab.1 Symbol description

Symbol	Description
σ	sigmoid activation function
Y_t	the observed value of the time series.
Δ	the differencing operation.
p	the order of autoregression (AR) part.

d	the order of differencing.
q	the order of the moving average (MA) part.
α	the autoregression coefficients.
β	the moving average coefficients.
ϵ_t	the white noise error.
n	the number of samples
p	the number of features
y_i	the actual output of the i-th observation
β_0	the intercept
x_{ij}	the value of the j-th feature for the i-th observation
β_j	the coefficient associated with the j-th feature
λ t	the regularization parameter used in Lasso regression

4 Model building and solution of Question 1

In order to analyze the main factors that affect the development trend of new energy electric vehicles in China, we can leverage the Grey relational analysis (GRA) model. GRA is well-suited for studying the intricate relationship among different factors influencing the development of new energy electric vehicles (NEEVs) in China.To ensure the effective application of the GRA model, our initial undertaking revolves around the identification and systematic collection of data spanning from 2013 to 2022.

We have compiled a comprehensive dataset encompassing various aspects such as electric vehicle performance, technological advancements and economic conditions for our research. By quantifying the degree of relevance of each factors using GRA model, we are able to obtain that the NEEVs sales is the most relevant to the development of NEEVs thus it can best indicate the development of NEEVs in China. Following the sales, the NEEVs ownership, energy efficiency and number of charging piles are also highly relevant to the NEEVs development.

4.1 Data Preparation

By consulting relevant sources and information, we selected 7 indicators as the factors affecting the development trend of NEEVs which included market performance metrics, infrastructure development, energy and sustainability. Due to the different dimensions of each indicator, the normalization operation needs to be carried out in order to unify the data to an approximate range.

Mean normalization method is used to reduce the data volatility. In essence, divide the data of each sequence by the mean of the sequence.

The division by mean:

$$x_i(k)' = \frac{x_i(k)}{mean(x_i)} \tag{1}$$

where $x_i(k)'$ is the normalized data.

The mean of i-th factor sequence:

$$\overline{x_i} = \frac{1}{n}\sum_{k=1}^{n} x_i(k) \tag{2}$$

where $x_i(k)$ is the original data, n is the total number of year.

Tab.2 The mean of each factor sequence

Factors	Mean
Sales	95.656
Vehicle Stock	352.9
Energy Efficiency	0.9642169
Charging Piles	109.18
Production Ratio	23
Charging Cost	0.76
Average Price	5.55

4.2 GRA Model Establishment

The GRA model will quantify the degree of similarity or correlation between each indicator and the reference series, facilitating a comprehensive analysis of the factors influencing the development of NEEVs in China.

Let X_0 be the reference series, representing the development trend of NEEVs in China. X_i represents various factors such as sales (i =1), NEEVs ownership (i =2), production ratio (i =3), charging piles(i =4), average price (i =5), charging cost(i =6) and energy efficiency (i =7).

The comparison sequence as follows:

$$|X_1' \quad X_2' \quad \cdots \quad X_n'| = \begin{bmatrix} x_1'(1) & x_2'(1) & \cdots & x_n'(1) \\ x_1'(2) & x_2'(2) & \cdots & x_n'(2) \\ \vdots & \vdots & & \vdots \\ x_1'(m) & x_2'(m) & \cdots & x_n'(m) \end{bmatrix} \tag{3}$$

The reference series：

$$X_0' = \left(x_0'(1), x_2'(2), \dots, x_0'(m)\right)^T \tag{4}$$

The grey relational coefficient of each comparison sequence X_i with the corresponding element of the reference series X_0 is calculated separately by the following formula:

$$\gamma\left(x_0(k), x_i(k)\right) = \frac{\Delta_{min} + \rho\Delta_{max}}{\Delta_{0i}(k) + \rho\Delta_{max}} \tag{5}$$

$$\Delta min = |x_0(k) - x_i(k)|$$

$$\Delta max = |x_0(k) - x_i(k)|$$

$$\Delta_{0i}(k) = |x_0(k) - x_i(k)|$$

Generally, we take the resolution coefficient $\rho = 0.5$.

The weighted average value of the correlation coefficient between each index and the corresponding element of the reference sequence is calculated respectively to reflect the correlation between each control device object and the reference sequence, and it is called the correlation degree, which is denoted as:

$$\gamma(x_0, x_i) = \frac{1}{N}\sum_{k=1}^{N} w_k \gamma\left(x_0(k), x_i(k)\right) \tag{6}$$

where w_k is the weight of the k-th data.

We use the formula to calculate the grey relational degree to rank the factors based on their grey relational coefficients. According to the grey weighted correlation degree of the calculated results, we established the association order of each evaluation object. The higher the correlation, the more significant the evaluation object is in relation to the evaluation criteria.

4.3 Solution of GRA Model

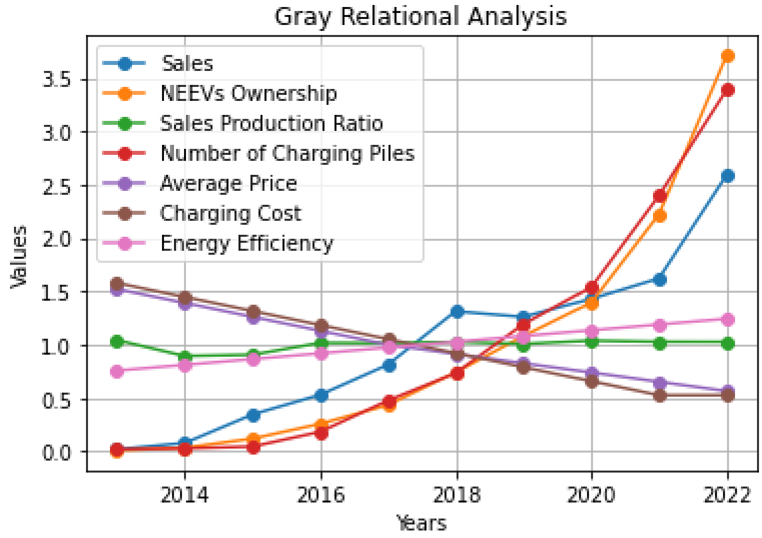

Fig.1 Grey Relational Coefficient Plot of New Electric Vehicles in China

According to the above figure, we can observe the correlation trends of seven indicators influencing the development of new energy vehicles from 2013 to 2022. In order to form a more intuitive correlation sequence, we calculated the average values of each factor across different dimensions, and the sorted results are shown in the table below:

Tab.2 Relevance results

No.	Factors	Degree of Relevance
1	Sales	1.00
2	NEEVs Ownership	0.87
3	Energy Efficiency	0.87
4	Number of Charging Piles	0.87
5	Sales Production Ratio	0.77
6	Charging Cost	0.47
7	Average Price	0.47

Based on the degree of relevance, we can conclude that the sales factor has the highest correlation with the development of NEEVs in China following by the NEEVs Ownership, Energy Efficiency of NEEVs and the Number of Charging Piles with 0.87 degree of relevance. Therefore, we can state that these 4 factors are the main factors affecting the development of NEEVs and that by making improvements on these factors should results in significant impact on the development of NEEVs in China.

5 Model building and solution of Question 2

The rapid evolution of China’s New Energy Electric Vehicle sector(NEEVs) industry has established its prominent position in the global automotive sector. To predict the future development trends of China's new energy vehicles over the next 10 years, we utilize historical data as the foundation to establish an ARIMA model for forecasting.

We collected 13 factors affecting the NEEVs industry development from year 2013 to 2022 and among them, we selected 6 indicators to predict the development of China's NEEV in the next 10 years. The 6 indicators are the number of NEEVs patent applications, NEEVs market penetration rate, NEEVs production, NEEVs ownership in China, charging cost and the number of charging piles. By using the ARIMA model, we are able to forecast the development of the 6 indicators from 2023 to 2032. In results, we can predict that the NEEVs production is expected to stabilize over the next decade. With a consistent production, the NEEVs ownership will steadily increase until it reaches a stable level.

5.1 Data Preparation

The prediction of China's NEEV industry development over the succeeding decade relies on the application of the ARIMA model, a proven statistical method for time series forecasting. This model integrates historical data on crucial factors such as infrastructure development, government policies, economic and technological advancements. By establishing the ARIMA model, we aim to capture and extrapolate patterns inherent in the historical data, providing valuable insights into the future of China's NEEV industry.

The AR model must satisfy the requirement of stationarity.
Determining an order denoted as ‘p’ is essential for the AR model, representing the count of past periods used to predict the current value.
The general formula for a Pth-order AR Component is defined as:

$$X_t = \alpha_1 X_{t-1} + \alpha_2 X_{t-2} + \cdots + \alpha_p X_{t-p} + u_t \tag{7}$$

Integrated(I) Component:

$$Y_t = \nabla X_t \tag{8}$$

In the process of data preprocessing, we differenced the non-stationary time series data until the time series became stationary, using first-order difference equations.

Moving Average(MA) Component:

$$X_t = \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_q\varepsilon_{t-q} \tag{9}$$

5.2 ARIMA Model Establishment

The Autoregressive Integrated Moving Average (ARIMA） model is a popular and widely used statistical analysis method for time series data forecasting. ARIMA model combines the concepts of AutoRegressive (AR), Integrated (I), and Moving Average (MA), enabling the handling of non-stationary time series and transforming them into stationary ones. In the ARIMA model, denoted as ARIMA(p,d,q):

$$\Delta^d Y_t = \alpha_1\Delta^{d-1}Y_{t-1} + \alpha_2\Delta^{d-1}Y_{t-2} + \cdots + \alpha_p\Delta^{d-1}Y_{t-p} + \epsilon_t - \beta_1\epsilon_{t-1} - \beta_2\epsilon_{t-2} - \cdots - \beta_q\epsilon_{t-q} \tag{10}$$

The basic idea of the ARIMA model is to adjust the values of the three parameters, p, d, and q to better fit historical data and enable predictions for the future.

5.3 Result

In results of the ARIMA model, we depicts the prediction of NEEVs development in China from 2023 to 2032 in the form of graph together with the existing data from 2013 to 2022 for better visualization of the development trends.

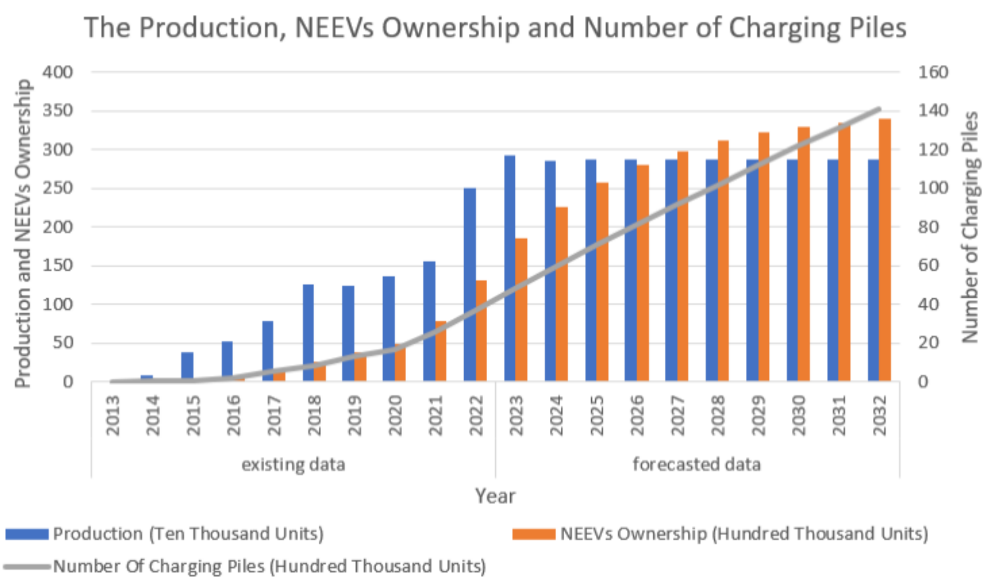

Fig.2 The Results of the Production, NEEVs Ownership and Number of Charging Piles Predictions

According to the above figure, the production of NEEVs shows an upward trend until 2023, after which the production stabilizes. Simultaneously, it is predicted that the ownership of NEEVs and the number of charging piles will steadily increase each year over the next 10 years. Therefore, we estimate that starting from 2023, the annual market demand for NEEVs will reach nearly 3 million according to the forecasted data, indicating a stable demand for NEEVs. Moreover, the popularity of NEEVs is increasing, as reflected in the yearly growth of NEEV ownership. Since the recognition of NEEV charging piles as one of China's seven major new infrastructure areas, the charging piles construction market has shown signs of significant growth.[2] According to our predictions, the number of charging stations, as one of the indicators of NEEV development, will continue to rise over the next 10 years, reaching millions in quantity.

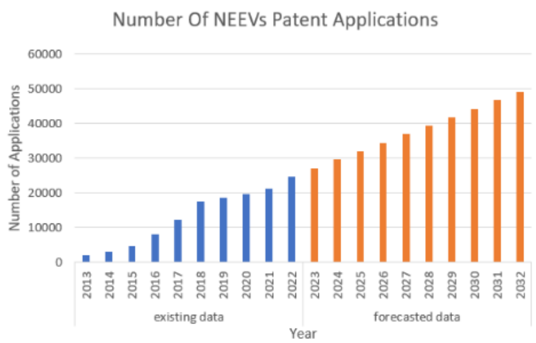

Fig3(a). The Results of the No. of NEEVs Patent Applications Prediction

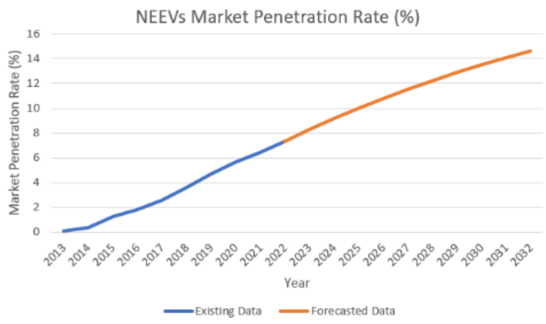

Fig3(b). The Results of NEEVs Market Penetration Rate Prediction

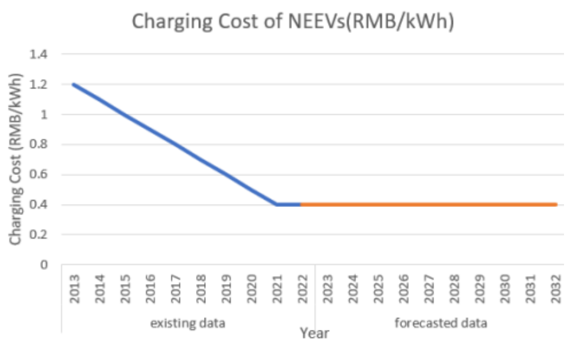

Fig3(c). The Results of the Charging Cost of NEEVs Prediction

Referring to figures (a) and (b), there is a consistent increase in the number of patent applications for NEEVs and the NEEVs Market Penetration Rate over time. According to First Capital Securities, the NEEVs Market Penetration Rate has consistently reached new highs in recent years,[1] and figure (b), representing the predicted trend for the NEEVs Market Penetration Rate over the next 10 years, indeed confirms this. Finally, figure (c) illustrates the trend of charging costs from 2013 to 2032. We predict that starting from 2023, charging costs will be maintained at the level of 0.4 RMB/kWh. As the market demand stabilizes, charging costs will also be maintained at a relatively economical price.

6 Model Building of Question 3 and Question 4 and Solution

In this paper, we leverage the same model to solve question 3 and question 4. Question 3 involves analyzing the impact of new energy electric vehicles (NEEVs) on the global traditional energy vehicle industry. Question 4 explores the effects of policies implemented by other countries to resist the development of NEEVs in China. Since both of these questions aim to quantitatively analyze the correlation relationships, we utilize Linear Regression to establish the model.

For Question 3,we get the results. For Question 4, We compare the growth rate and number of NEEVs exported by China to the other countries before and after the implementation of the policy.

6.1 Data Description for Question 4

Question 4 examines the impact of foreign resistance policies against the development of China's NEEVs industry. In this question, we found the information regrading the European Union’s (EU) implementation of policies resisting China's NEEVs.

In the investigation of Question 4, we have identified news and articles related to foreign resistance policies against the development of China's NEEVs. According to the content published by the law firm Zhong Lun in the CGGT think tank, we discovered that the EU intermittently conducted anti-dumping and anti-subsidy investigations on China from 2017 to 2022, which commonly known as the 'double-reverse' investigation.

Due to the rapid development of China's new energy vehicle industry in recent years, the scale of exports of new energy vehicles has expanded rapidly in the short term. This is inevitably impacting enterprises in importing countries that domestically produce similar products, leading to deterioration in important operational indicators such as sales volume, market share, and profitability. Although there is no clear data indicating the impact on the EU's automotive industry, several EU countries have expressed dissatisfaction with the large influx of new energy vehicles from China, as reported by articles. According to information released by the National Development and Reform Commission, China's total exports of new energy vehicles to the EU account for approximately 44%, making it a major market for China's export of new energy vehicles. Taking the example of anti-dumping investigations, the EU initiated investigations into components of new energy vehicles, such as steel wheels, for approximately 12.8 months in the compiled data. Punitive tax rates of 66.40% were imposed on responding enterprises importing to the EU.

6.2 Linear Regression Model Establishment

We simplify the issue by considering a linear model that encompasses multiple influencing factors. Assuming the primary factors affecting the development of new energy electric vehicles are government policies, economic, market demand, technological advancement, etc., we can utilize the following linear model:

$$Y = \beta_0 + \beta_1 X_1 + \beta_3 X_3 + \beta_4 X_4 + \alpha \sum_{i=1}^{4} \beta_i^2 \tag{11}$$

For Question 3, we let the global traditional car sales be Y. The coefficients $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$ in the model represent the effect of the corresponding variable, such as policy,,market demand and technological advancement to the development of NEEVs. $\alpha \sum_{i=1}^{4} \beta_i^2$ is the different of model.

Lasso regression:

$$minimize\left(\frac{1}{2n}\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\,\beta_j\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j|\right) \tag{12}$$

6.3 Solution of Question 3

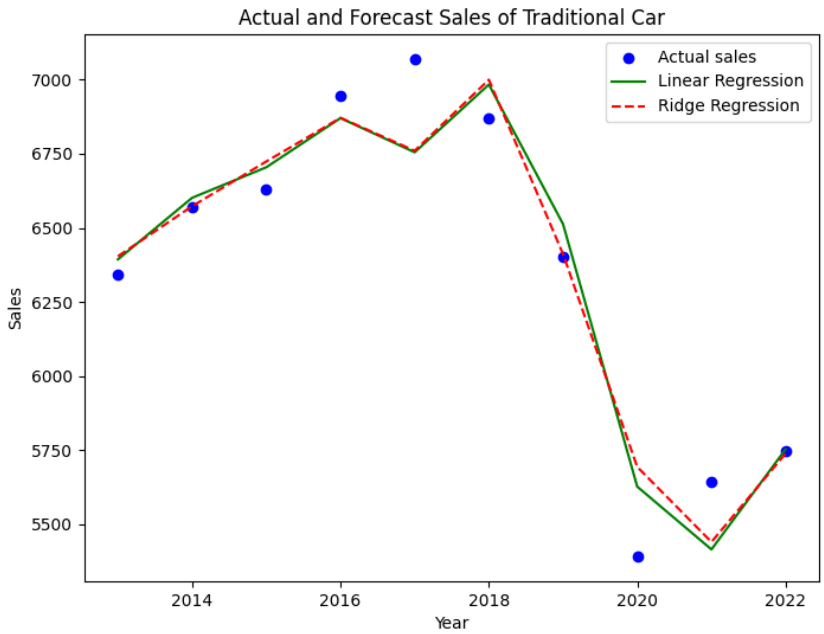

Fig.4 Actual and Forecast Sales of Traditional Car on The Effect of NEEVs Developments

Referring to the above figure, we can conclude that the linear regression model in question three can make predictions about the global conventional car sales changes based on indicators influencing the development of NEEVs. Moreover, the predicted results exhibit a similar trend to the actual sales. Therefore, we can infer that with the development of NEEVs, global conventional car sales have experienced significant fluctuations since 2018, with a noticeable decline in sales.

6.4 Solution of Question 4

When not considering the resistance policy, the average sales growth rate of NEEVs in EU countries and the average sales growth rate of NEEVs in China are as follows:

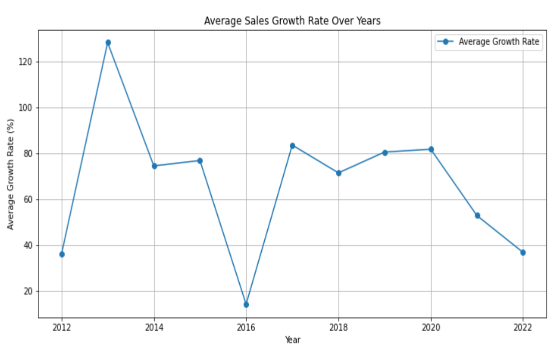

Fig.5 Average Sales Growth Rate of The European Union without Policy Indicator

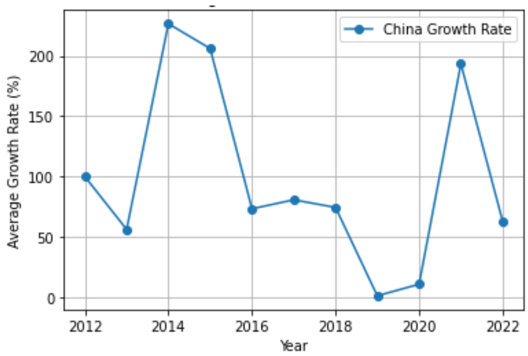

Fig.6 Average Sales Growth Rate of China without Policy Indicator

After incorporating the resistance policy into the model, we predict the sales growth rate of global NEEVs to be:

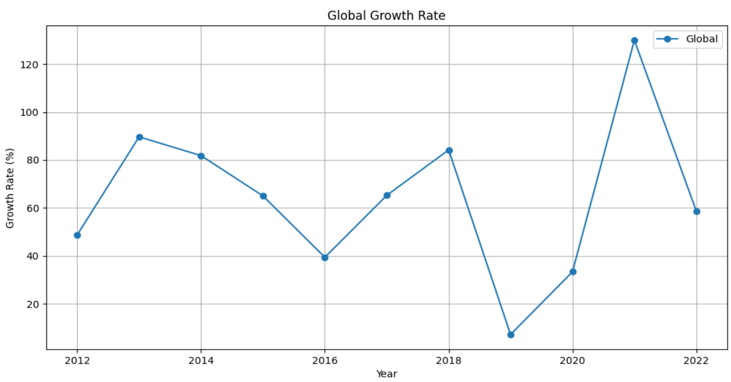

Fig.7 Global Growth Rate of Sales with Policy Indicator

And the global sales of NEEVs considering the resistance policy indicator and the sales of NEEVs in China without considering the boycott policy indicator are:

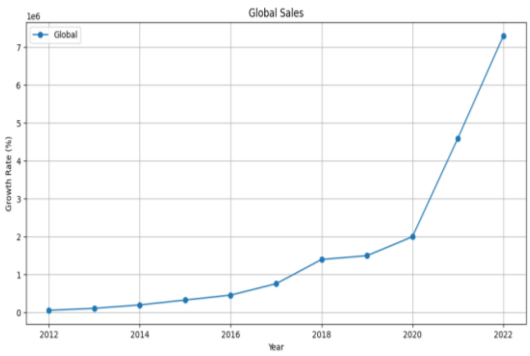

Fig.8 Global Sales with Policy Indicator

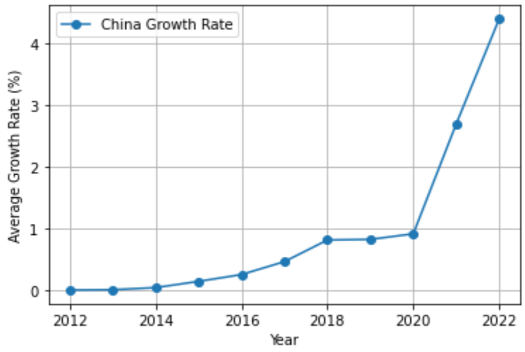

Fig.9 Average Sales Growth of China without Policy Indicator

By comparing the above figures, we can see that when not including the resistance policy as an indicator in the sales forecasting model, the sales trends of NEEVs in China and the globally forecasted NEEVs sales curve with the resistance policy as an indicator are consistent. Therefore, we can understand that the resistance policy is not expected to have a significant impact on the development of NEEVs in China.

6.5 Model Checking

For Question 3, we use Mean Squared Error(MSE) and R^2 to assess the performance of regression models.

The formula of R^2 (Coefficient of Determination):

$$R^2 = 1 - \frac{\sum_i (\hat{y}_i - y_i)^2}{\sum_i (\bar{y}_i - y_i)^2} \tag{13}$$

The value range of R^2 is [0,1]. A value close to 0 indicates a poor fit of the model, while a value close to 1 signifies a model that accurately predicts the observed outcomes.

MSE represents the average of the squared differences between observed and predicted values, with smaller values indicating better model performance.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{14}$$

where n is the number of samples, y_i is the observed value, and $\hat{y}_i$ is the predicted value.

Tab. 4 Model Checking based on the impact of NEEVs on Global Traditional Vehicles

	Linear Progression Model	Lasso Regression Model
Coefficient（Slope）	[1.39190983e+02 - 9.64990386e+01	[8.80898812e+01 - 4.77885653e+01

	1.63727303e+02 - 1.89226037e+02 -1.12330955e-01 4.02244754e-01 1.92378945e-02]	1.32391795e+02 -1.47578460e+02 - 1.05482432e-01 3.28367002e-01 1.29581787e-02]
Intercept	6700.507701877405	6840.810966254142
MSE	24631.575372392537	26343.992185232317
R^2	0.9192760060167888	0.913663976643655

Based on the model checking results presented in the tab.4, it is evident that the R^2 value is close to 1, indicating a high level of accuracy and minimal errors in the model.

7 Model Building and Solution of Question 5

To address the fifth question, we collected population data for cities with populations exceeding 1 million in various countries, along with data on carbon emissions, emissions of four automobile exhaust pollutants, and the ownership of new energy vehicles (NEEVs) and electric vehicles. Through data analysis, we aim to correlate the relationship between population and ownership, the relationship between carbon emissions and pollutant emissions, and how these two relationships mutually influence each other. By doing so, we can predict the impact of different scales of new energy vehicles on carbon emissions and pollutant emissions when a city's population reaches 1 million. This analysis helps us understand the ecological impact of NEEV electrification on the environment of that city.

In this Green Vehicle Popularization and Environmental Impact Model, the projections exhibit a consistent rise in the adoption of pure energy vehicles and NEEVs, accompanied by a reduction in carbon and exhaust pollutant emissions. This illustrates the positive contribution of NEEVs towards enhancing air quality and advancing environmental preservation.

7.1 Green Vehicle Popularization and Environmental Impact Model

In this model we do the simple mathematical calculations. First of all, the formula is used to calculate the proportion of energy vehicles in various categories.

Ratios Calculation:

$$NEEVs\_100 = \left(\frac{\text{NEEVsOwnership}}{\text{Population}}\right) \times 1000000$$

$$PureElectricVehicle\_100 = \left(\frac{\text{PureElectricVehicleOwnership}}{\text{Population}}\right) \times 1000000$$

$$MotorVehicles\_100 = \left(\frac{\text{MotorVehiclesOwnership}}{\text{Population}}\right) \times 1000000$$

$$NEEVs\_100\_normalized = \frac{\text{NEEVs\_100}}{\text{MotorVehicles\_100}}$$

$$PureElectricVehicle_{1}00_{n}ormalized = \frac{\text{PureElectricVehicle\_100}}{\text{MotorVehicles\_100}} \tag{15}$$

Calculation of CO_2 Emissions per Unit GDP:

$$CO_2Emissions_GDP = \frac{\text{CO2Emissions}}{\text{Population}} \times 1000000 \tag{16}$$

This equation is used to evaluate the impact of economic activities on CO_2emissions in a country or region. This formula calculates the CO_2emissions (CO_2Emissions) per unit of population (Population) in millions (1,000,000 units).

Calculation of Total Emissions of Four Pollutants

$$TotalEmissions = CO + VOC + NO_x + PM \tag{17}$$

This formula represents the total emissions of four major pollutants (TotalEmissions), including Carbon Monoxide (CO), Volatile Organic Compounds (VOC), Nitrogen Oxides (NOx), and Particulate Matter (PM). Then, we compare the images based on the analysis output.

7.2 Solution of Question 5

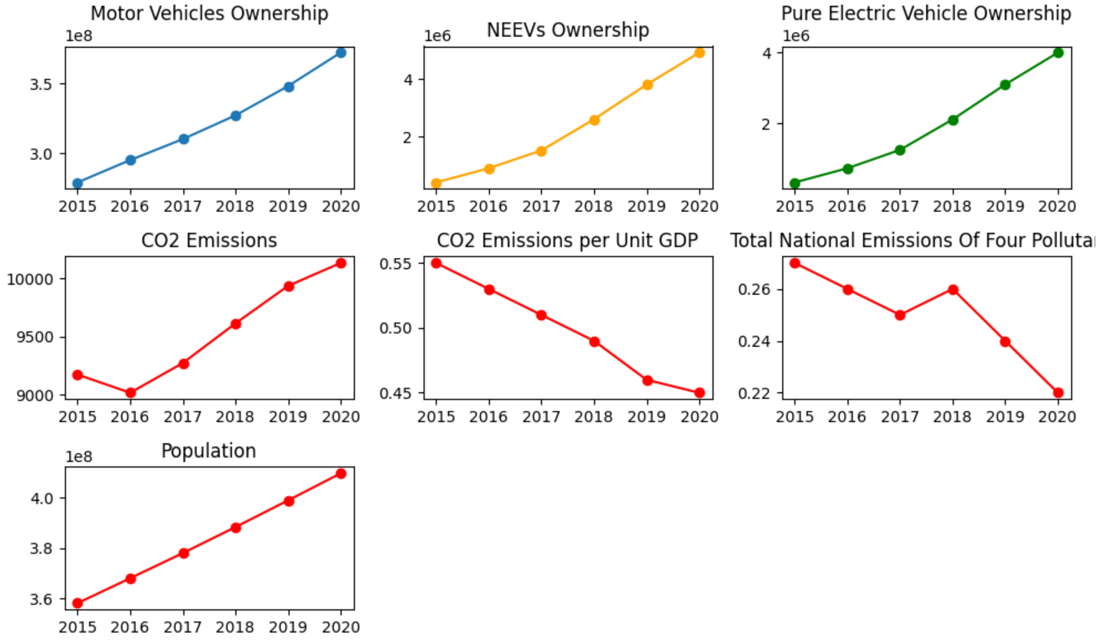

Fig.10 Results of Questions 5 Indicators from 2015-2020

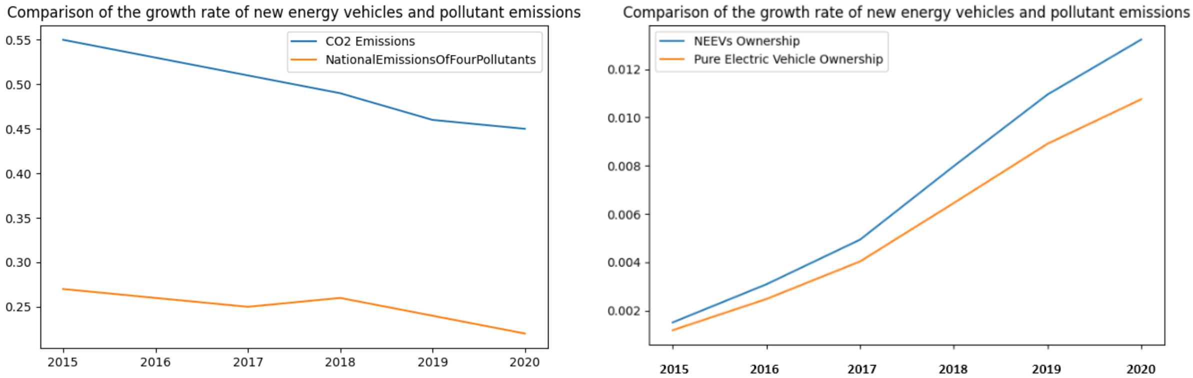

Fig.11 Comparison of the Growth Rate of NEEVs and Pollutant Emissions of A City with 1 Million Populations

As depicted in the above figure, we estimated the ownership of New Energy Electric Vehicles (NEEVs) and pure electric vehicles in a city with a population of one million from 2015 to 2020. We also examined the impact of ownership on carbon emissions and exhaust pollutant emissions in the city. The results indicate that when the ownership of pure electric vehicles approaches that of NEEVs, meaning that a significant portion of NEEVs in the city are pure electric vehicles and the ownership is increasing annually, both carbon emissions and exhaust pollutant emissions in the city decrease over the same time series. Therefore, we can conclude that the electrification of NEEVs has a positive impact on the ecological environment of the city.

8 An Open Letter: Embracing a Green Tomorrow --- The Impact of Electric Vehicles on Our City and Planet

Dear Residents,

Greetings!

Today, I want to discuss the positive transformations brought about by new energy electric vehicles and their profound impact on our city and the global environment.

As technology advances and environmental awareness increases, new energy electric vehicles are emerging as a fresh option for urban transportation. In comparison to traditional fuel vehicles, electric vehicles generate nearly zero exhaust emissions during operation, leading to a significant reduction in air pollutant emissions. Our research indicates that with the growing number of electric vehicles, the city's air quality has visibly improved, accompanied by a substantial decrease in carbon emissions. Electric vehicles not only represent a shift in transportation methods but also signify a transformation in our lifestyle. They signify a solid step forward in our pursuit of a greener, more sustainable future.

Internationally, an increasing number of countries and cities are implementing measures to encourage the development of electric vehicles. Through policy support and infrastructure development, we are collectively fostering the rapid growth of this industry. With government backing and citizen participation, electric vehicles are progressively becoming integral to urban transportation.

Lastly, I extend an invitation to every citizen to join this green revolution. Let us collectively opt for electric vehicles and make substantial contributions to our city and our planet. Our individual choices will collectively shape a better and cleaner world for generations to come.

Thank you for your time and support!

Sincerely yours,

9 References

[1] Chen Qi. Shouchuang Securities: Global new energy vehicle sales are expected to reach 18 million units by 2025[J]. Automotive and Accessories, 2021(19):43. DOI:10.3969/j.issn.1006-0162.2021.19.010.

[2] Chen Xiujuan. Charging piles usher in a second spring[J]. Automotive Observation, 2020(4):101. DOI:10.3969/j.issn.1673-145X.2020.04.041.

Appendix

Software Used: PyCharm

Question 1 code:

```python
import numpy as np
import matplotlib.pyplot as plt

from scipy.stats import rankdata

def createData():

    referenceData = {

        'year': np.array([2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022]),
        'sales': np.array([0.018399, 0.078406, 0.346032, 0.530024, 0.812286, 1.313038, 1.260768, 1.429079, 1.621435, 2.590533])
    }

    data = {

        'sales': np.array([0.018399, 0.078406, 0.346032, 0.530024, 0.812286, 1.313038, 1.260768, 1.429079, 1.621435, 2.590533]),
        'NEEVs': np.array([0.008501, 0.034004, 0.119014, 0.257863, 0.433551, 0.739586, 1.079626, 1.394163, 2.221593, 3.7121]),
        'production_ratio': np.array([1.043037, 0.894061, 0.905762, 1.017051, 1.014905, 1.025678, 1.007049, 1.03787, 1.027833, 1.026752]),
        'charging_piles': np.array([0.02015, 0.027478, 0.04488, 0.183184, 0.476278, 0.732735, 1.190694, 1.538743, 2.396959, 3.388899]),
        'average_price': np.array([1.521739, 1.391304, 1.26087, 1.130435, 1, 0.913043, 0.826087, 0.73913, 0.652174, 0.565217]),
        'charging_cost': np.array([1.578947, 1.447368, 1.315789, 1.184211, 1.052632, 0.921053, 0.789474, 0.657895, 0.526316, 0.526316]),
        'energy_efficiency': np.array([0.756757, 0.810811, 0.864865, 0.918919, 0.972973, 1.027027, 1.081081, 1.135135, 1.189189, 1.243243])
    }
```

```

    return referenceData, data

def calculateGray(referenceData, data, dataKey):

    refRank  = rankdata(data['sales'])
    dataRank = rankdata(data[dataKey])

    d = np.abs(refRank - dataRank)
    minD = np.min(d)
    maxD = np.max(d)

    grayRelationDegree = (maxD - d + 0.5) / (maxD + 0.5)

    return grayRelationDegree.mean()

def plotGray(year, data, dataKey, label):

    plt.plot(year, data[dataKey], marker='o', label=label)

if __name__ == '__main__':

    referenceData, data = createData()

    plotGray(referenceData['year'], data, 'sales'             ,  'Sales'                    )
    plotGray(referenceData['year'], data, 'NEEVs'             , 'NEEVs Ownership'           )
    plotGray(referenceData['year'], data, 'production_ratio'  , 'Sales Production Ratio'    )
    plotGray(referenceData['year'], data, 'charging_piles'    , 'Number of Charging Piles')
    plotGray(referenceData['year'], data, 'average_price'     , 'Average Price'             )
    plotGray(referenceData['year'], data, 'charging_cost'     , 'Charging Cost'             )
    plotGray(referenceData['year'], data, 'energy_efficiency', 'Energy Efficiency'          )

    plt.legend()
    plt.xlabel('Years')
    plt.ylabel('Values')

    plt.title('Grey Relational Analysis')
```

```
    plt.grid(True)
    plt.show()
```

Question 2 code:

```
import pandas as pd
import numpy as np
from statsmodels.tsa.arima.model import ARIMA
import matplotlib.pyplot as plt

data = {
    'Year': [2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022],
    'New Energy Car Companies': [300, 500, 800, 1200, 1500, 1800, 2000, 2200, 2400, 2600],
    'Market Size (thousand units)': [5, 15, 50, 120, 250, 400, 600, 800, 1000, 1200],
    'Industry Chain Size': [230, 280, 320, 370, 420, 460, 500, 550, 590, 630],
    'New Energy Car Patent Applications': [2024, 3111, 4566, 8205, 12262, 17647, 18498, 19739, 21300, 24700],
    'Market Share': [0.9, 1.3, 2.5, 3.1, 5.3, 7.2, 9.7, 11.4, 13.4, 25.6],
    'Market Penetration Rate': [0.1, 0.4, 1.3, 1.8, 2.6, 3.6, 4.7, 5.7, 6.4, 7.3],
    'Production (thousand units)': [1.75, 8.7, 37.9, 51.7, 79.4, 127, 124.2, 136.6, 156.5, 250.3],
    'Sales (thousand units)': [1.76, 7.5, 33.1, 50.7, 77.7, 125.6, 120.6, 136.7, 155.1, 247.8],
    'Inventory (thousand units)': [3, 12, 42, 91, 153, 261, 381, 492, 784, 1310],
    'Average Price (thousand RMB)': [35, 32, 29, 26, 23, 21, 19, 17, 15, 13],
    'Government Subsidy Amount (billion RMB)': [30, 50, 70, 100, 120, 140, 160, 180, 200, 220],
    'Charging Cost (RMB/kWh)': [1.2, 1.1, 1, 0.9, 0.8, 0.7, 0.6, 0.5, 0.4, 0.4],
    'Charging Piles Quantity (ten thousand)': [2.2, 3, 4.9, 20, 52, 80, 130, 168, 261.7, 370]
}

df = pd.DataFrame(data)
df['Year'] = pd.to_datetime(df['Year'], format='%Y')
df = df.set_index('Year')

```

```
def arima_forecast(data, steps):
    model = ARIMA(data, order=(1, 1, 1))
    results = model.fit()
    forecast = results.get_forecast(steps=steps)
    forecast_index = pd.date_range(start=data.index[-1], periods=steps + 1, freq='Y')[1:]
    forecast_mean = forecast.predicted_mean.values
    forecast_df = pd.DataFrame({'Forecast': forecast_mean}, index=forecast_index)
    return forecast_df

forecast_years = 13

for column_name in df.columns:
    plt.figure(figsize=(12, 6))

    plt.plot(df.index, df[column_name], label='Existing Data', color='blue')

    forecast_data = arima_forecast(df[column_name].loc['2020':], forecast_years)
    plt.plot(forecast_data.index, forecast_data['Forecast'], label='Forecasted Data', color='orange')

    plt.title(f'{column_name}')
    plt.xlabel('Year')
    plt.ylabel('Value')
    plt.legend()
    plt.show()

    print(f"{column_name} (2020-2032):")
    print(forecast_data)
    print("\n")
```

	Year	Number Of	Market Pe	Productic	NEEVs Owr	Charging	Number Of Charging Piles (Hundred Thousand Units)
	2013	2024	0. 1	1. 75	0.3	1. 2	0.22
	2014	3111	0. 4	8. 7	1.2	1. 1	0.3
	2015	4566	1. 3	37. 9	4.2	1	0.49
	2016	8205	1. 8	51. 7	9.1	0. 9	2
existing dat	2017	12262	2. 6	79. 4	15.3	0. 8	5.2
	2018	17647	3. 6	127	26.1	0. 7	8
	2019	18498	4. 7	124. 2	38.1	0. 6	13
	2020	19739	5. 7	136. 6	49.2	0. 5	16.8
	2021	21300	6. 4	156. 5	78.4	0. 4	26.17
	2022	24700	7. 3	250. 3	131	0. 4	37
	2023	27148.11	8.256343	293.7375	185.4724	0.4	48.38762
	2024	29596.18	9.154103	285.5605	226.5546	0.4	59.54144
	2025	32044.16	9.996867	287.0998	257.538	0.4	70.46627
	2026	34492.07	10.788	286.81	280.9052	0.4	81.1668
	2027	36939.9	11.53068	286.8646	298.5283	0.4	91.64765
	2028	39387.67	12.22786	286.8543	311.8194	0.4	101.9133
recasted da	2029	41835.36	12.88233	286.8562	321.8432	0.4	111.9682
	2030	44282.98	13.4967	286.8559	329.4031	0.4	121.8167
	2031	46730.53	14.07345	286.8559	335.1046	0.4	131.463
	2032	49178	14.61486	286.8559	339.4046	0.4	140.9112
	2033	51625.41	15.1231	286.8559	342.6475	0.4	150.1654
	2034	54072.74	15.60022	286.8559	345.0933	0.4	159.2297
	2035	56520	16.0481	286.8559	346.9379	0.4	168.1079

Question 3 code:

```
import numpy as np
import pandas as pd
from sklearn.linear_model import LinearRegression, Ridge
from sklearn.metrics import mean_squared_error, r2_score
import matplotlib.pyplot as plt

# Assuming this is the collected data (example data, actual data may vary)
data = {
    'Year': np.arange(2013, 2023),
    'TraditionalCarSales': [6342.92,6570.82,6631.42,6946.44,7069.48,6869.05 ,6403.35,5391.59,5643.78,5748.54],
    'MarketShare': [0.9,1.3,2.5,3.1,5.3,7.2,9.7,11.4,13.4,25.6],
    'MarketPenetration': [0.1,0.4,1.3,1.8,2.6,3.6,4.7,5.7,6.4,7.3],
    'NewCarProduction':[1.75,8.7,37.9,51.7,79.4,127,124.2,136.6,156.5,250.3],
    'NewCarSales': [1.76, 7.5, 33.1, 50.7, 77.7, 125.6, 120.6, 136.7, 155.1, 247.8],
    'EffectivePatent': [11605.00,14106.00,18840.00,23194.00,34481.00,45168.00,57360.00,62403.00,71478.00,80855.00],
    'PatentCount':[2024,3111,4566,8205,12262,17647,18498,19739,21300,24700],
    'GlobalPowerDemand':[5900,4500,6200,18000,11000,30000,21000,24000,34000,65000],
}

```

```
# Create DataFrame
df = pd.DataFrame(data)

# Split data into features (X) and target variable (Y)
X = df[['MarketShare','MarketPenetration','NewCarProduction','NewCarSales','EffectivePatent','PatentCount','GlobalPowerDemand']]
Y = df['TraditionalCarSales']


# 建立线性回归模型
model = LinearRegression()
model.fit(X, Y)

# 输出模型参数
print('线性回归模型系数（斜率）: ', model.coef_)
print('线性回归模型截距: ', model.intercept_)

# 进行预测
Y_pred = model.predict(X)

# 模型评估
mse = mean_squared_error(Y, Y_pred)
r2 = r2_score(Y, Y_pred)
print('线性回归模型均方误差 (MSE): ', mse)
print('线性回归模型 R^2 得分: ', r2)

# 使用岭回归建立模型
ridge_model = Ridge(alpha=1.0)  # 可以调整 alpha 参数
ridge_model.fit(X, Y)

# 输出岭回归模型参数
print('岭回归模型系数（斜率）: ', ridge_model.coef_)
print('岭回归模型截距: ', ridge_model.intercept_)

# 进行岭回归预测
Y_pred_ridge = ridge_model.predict(X)
# 模型评估（均方误差和 R^2 得分）
mse_ridge = mean_squared_error(Y, Y_pred_ridge)
r2_ridge = r2_score(Y, Y_pred_ridge)
print('岭回归均方误差 (MSE): ', mse_ridge)
print('岭回归 R^2 得分: ', r2_ridge)

# 绘制实际销量与预测销量的图表
```

```python
plt.figure(figsize=(8, 6))
plt.scatter(df['Year'], Y, color='blue', label='Actual sales')
plt.plot(df['Year'], Y_pred, color='green', linestyle='-', label='Linear Regression')
plt.plot(df['Year'], Y_pred_ridge, color='red', linestyle='--', label='Ridge Regression')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.title('Actual and Forecast Sales of Traditional Car')
plt.legend()
plt.show()
```

```
线性回归模型系数（斜率）： [ 1.39190983e+02 -9.64990386e+01  1.63727303e+02 -1.89226037e+02
 -1.12330955e-01  4.02244754e-01  1.92378945e-02]
线性回归模型截距： 6700.507701877405
线性回归模型均方误差 (MSE): 24631.575372392537
线性回归模型R^2得分： 0.9192760060167888
岭回归模型系数（斜率）： [ 8.80898812e+01 -4.77885653e+01  1.32391795e+02 -1.47578460e+02
 -1.05482432e-01  3.28367002e-01  1.29581787e-02]
岭回归模型截距： 6840.810966254142
岭回归均方误差 (MSE): 26343.992185232317
岭回归R^2得分： 0.913663976643655
```

Question 4 code:

```python
import numpy as np
import matplotlib.pyplot as plt

# 罗列数据
globalYear  = np.array([2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022])
globalSales = np.array([7200.00, 39000.00, 58000.00, 110000.00, 200000.00, 330000.00, 460000.00, 760000.00, 1400000.00, 1500000.00, 2000000.00, 4600000.00, 7300000.00])

chinaSales       = np.array([1100.00, 4800.00, 9600.00, 15000.00, 49000.00, 150000.00, 260000.00, 470000.00, 820000.00, 830000.00, 920000.00, 2700000.00, 4400000.00])
netherlandsSales = np.array([120.00, 860.00, 790.00, 2600.00, 2700.00, 3800.00, 4100.00, 9200.00, 24000.00, 62000.00, 73000.00, 64000.00, 73000.00])
spainSales       = np.array([76.00, 390.00, 430.00, 810.00, 1400.00, 1300.00, 2000.00, 3900.00, 6000.00, 10000.00, 18000.00, 24000.00, 33000.00])
```

```python
portugalSales     = np.array([720.00, 190.00, 52.00, 170.00, 190.00, 640.00, 810.00, 1900.00, 4100.00, 6900.00, 7800.00, 13000.00, 18000.00])
germanySales      = np.array([140.00, 1400.00, 2200.00, 5200.00, 9100.00, 12000.00, 11000.00, 25000.00, 36000.00, 63000.00, 190000.00, 360000.00, 470000.00])
norwaySales       = np.array([360.00, 2000.00, 3900.00, 7900.00, 20000.00, 26000.00, 24000.00, 33000.00, 46000.00, 60000.00, 77000.00, 110000.00, 150000.00])
swedenSales       = np.array([4.00, 180.00, 270.00, 430.00, 1200.00, 3000.00, 2900.00, 4400.00, 7100.00, 16000.00, 28000.00, 57000.00, 96000.00])
franceSales       = np.array([190.00, 2600.00, 5700.00, 8800.00, 11000.00, 17000.00, 22000.00, 25000.00, 31000.00, 43000.00, 110000.00, 160000.00, 210000.00])

# 计算增长率
def calculate_growth_rate(sales):
    return np.diff(sales) / sales[:-1] * 100

# 计算各国增长率
global_growth_rates = calculate_growth_rate(globalSales[1:])
china_growth_rates = calculate_growth_rate(chinaSales[1:])
netherlands_growth_rates = calculate_growth_rate(netherlandsSales[1:])
spain_growth_rates = calculate_growth_rate(spainSales[1:])
portugal_growth_rates = calculate_growth_rate(portugalSales[1:])
germany_growth_rates = calculate_growth_rate(germanySales[1:])
norway_growth_rates = calculate_growth_rate(norwaySales[1:])
sweden_growth_rates = calculate_growth_rate(swedenSales[1:])
france_growth_rates = calculate_growth_rate(franceSales[1:])

# 绘制全球增长率
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], global_growth_rates, label='Global', marker='o')
plt.title('Global Growth Rate')
plt.xlabel('Year')
plt.ylabel('Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()
```

```python

# 绘制全球销量变化
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], globalSales[2:], label='Global', marker='o')
plt.title('Global Sales')
plt.xlabel('Year')
plt.ylabel('Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()

# 绘制中国增长率
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], china_growth_rates, label='China', marker='o')
plt.title('Global Growth Rate')
plt.xlabel('Year')
plt.ylabel('Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()

# 绘制中国销量变化
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], chinaSales[2:], label='China', marker='o')
plt.title('China Sales')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

# 绘制欧盟各国增长率
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], netherlands_growth_rates, label='Netherlands', marker='o')
plt.plot(globalYear[2:], spain_growth_rates, label='Spain', marker='o')
plt.plot(globalYear[2:], portugal_growth_rates, label='Portugal', marker='o')
plt.plot(globalYear[2:], germany_growth_rates, label='Germany', marker='o')
```

```python
plt.plot(globalYear[2:], norway_growth_rates, label='Norway', marker='o')
plt.plot(globalYear[2:], sweden_growth_rates, label='Sweden', marker='o')
plt.plot(globalYear[2:], france_growth_rates, label='France', marker='o')
plt.title('Growth Rate Over Years')
plt.xlabel('Year')
plt.ylabel('Growth Rate')
plt.legend()
plt.grid(True)
plt.show()

# 绘制欧盟平均增长率
average_growth_rates = np.mean([netherlands_growth_rates, spain_growth_rates, portugal_growth_rates, germany_growth_rates, norway_growth_rates, sweden_growth_rates, france_growth_rates], axis=0)
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], average_growth_rates, label='Average', marker='o')
plt.title('Average Sales Growth Rate')
plt.xlabel('Year')
plt.ylabel('Average Growth Rate (%)')
plt.legend()
plt.grid(True)
plt.show()

# 绘制欧盟各国销量变化
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], netherlandsSales[2:], label='Netherlands', marker='o')
plt.plot(globalYear[2:], spainSales[2:], label='Spain', marker='o')
plt.plot(globalYear[2:], portugalSales[2:], label='Portugal', marker='o')
plt.plot(globalYear[2:], germanySales[2:], label='Germany', marker='o')
plt.plot(globalYear[2:], norwaySales[2:], label='Norway', marker='o')
plt.plot(globalYear[2:], swedenSales[2:], label='Sweden', marker='o')
plt.plot(globalYear[2:], franceSales[2:], label='France', marker='o')
```

```
plt.title('Sales')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

# 绘制欧盟平均销量
average_sales = np.mean([netherlandsSales[2:], spainSales[2:], portugalSales[2:], germanySales[2:], norwaySales[2:], swedenSales[2:], franceSales[2:]], axis=0)
plt.figure(figsize=(12, 6))
plt.plot(globalYear[2:], average_sales, label='Average', marker='o')
plt.title('Average Sales')
plt.xlabel('Year')
plt.ylabel('Average Sales')
plt.legend()
plt.grid(True)
plt.show()

# 计算出线性回归模型

# 选择数据
selectedYear = np.where((globalYear >= 2011) & (globalYear <= 2017))[0]
selectYear   = globalYear[selectedYear]

selectGlobalSales = globalSales[selectedYear]

selectChinaSales = chinaSales[selectedYear]

selectNetherlandsSales = netherlandsSales[selectedYear]
selectSpainSales       = spainSales[selectedYear]
selectPortugalSales    = portugalSales[selectedYear]
selectGermanySales     = germanySales[selectedYear]
selectNorwaySales      = norwaySales[selectedYear]
selectSwedenSales      = swedenSales[selectedYear]
selectFranceSales      = franceSales[selectedYear]

# 计算线性回归模型
globalSlope, globalIntercept = np.polyfit(selectYear, selectGlobalSales, 1)

```

```
chinaSlope, chinaIntercept = np.polyfit(selectYear, selectChinaSales, 1)

netherlandsSlope, netherlandsIntercept = np.polyfit(selectYear, selectNetherlandsSales, 1)
spainSlope       , spainIntercept       = np.polyfit(selectYear, selectSpainSales      , 1)
portugalSlope    , portugalIntercept    = np.polyfit(selectYear, selectPortugalSales   , 1)
germanySlope     , germanyIntercept     = np.polyfit(selectYear, selectGermanySales    , 1)
norwaySlope      , norwayIntercept      = np.polyfit(selectYear, selectNorwaySales     , 1)
swedenSlope      , swedenIntercept      = np.polyfit(selectYear, selectSwedenSales     , 1)
franceSlope      , franceIntercept      = np.polyfit(selectYear, selectFranceSales     , 1)

futureYear = np.array([2012, 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021, 2022, 2023])

predictedGlobalSales = globalSlope * futureYear + globalIntercept

predictedChinaSales = chinaSlope * futureYear + chinaIntercept

predictedNetherlandsSales = netherlandsSlope * futureYear + netherlandsIntercept
predictedSpainSales       = spainSlope       * futureYear + spainIntercept
predictedPortugalSales    = portugalSlope    * futureYear + portugalIntercept
predictedGermanySales     = germanySlope     * futureYear + germanyIntercept
predictedNorwaySales      = norwaySlope      * futureYear + norwayIntercept
predictedSwedenSales      = swedenSlope      * futureYear + swedenIntercept
predictedFranceSales      = franceSlope      * futureYear + franceIntercept

# 绘制全球未来销量
plt.figure(figsize=(12, 6))
```

```
plt.plot(futureYear, predictedGlobalSales, label='Predicted', linestyle='dashed', color='red')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

# 打印预测值
print('Global')
for year, sales in zip(futureYear, predictedGlobalSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')

# 绘制中国未来销量
plt.figure(figsize=(12, 6))
plt.plot(futureYear, predictedChinaSales, label='Predicted', linestyle='dashed', color='red')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

# 打印预测值
print('China')
for year, sales in zip(futureYear, predictedChinaSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')

# 绘制欧盟各国未来销量
plt.figure(figsize=(12, 6))
plt.plot(futureYear, predictedNetherlandsSales, label='Netherlands')
plt.plot(futureYear, predictedSpainSales, label='Spain')
plt.plot(futureYear, predictedPortugalSales, label='Portugal')
plt.plot(futureYear, predictedGermanySales, label='Germany')
plt.plot(futureYear, predictedNorwaySales, label='Norway')
plt.plot(futureYear, predictedSwedenSales, label='Swenden')
plt.plot(futureYear, predictedFranceSales, label='France')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
```

```python
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

# 打印预测值
print('Netherlands')
for year, sales in zip(futureYear, predictedNetherlandsSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('Spain')
for year, sales in zip(futureYear, predictedSpainSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('Portugal')
for year, sales in zip(futureYear, predictedPortugalSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('Germany')
for year, sales in zip(futureYear, predictedGermanySales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('Norway')
for year, sales in zip(futureYear, predictedNorwaySales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('Sweden')
for year, sales in zip(futureYear, predictedSwedenSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')
print('France')
for year, sales in zip(futureYear, predictedFranceSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')

# 绘制欧盟未来平均销量
# 绘制欧盟未来平均销量
plt.figure(figsize=(12, 6))
averageFutureSales = np.mean([predictedNetherlandsSales, predictedSpainSales, predictedPortugalSales, predictedGermanySales, predictedNorwaySales, predictedSwedenSales, predictedFranceSales], axis=0)
plt.plot(futureYear, averageFutureSales, label='Average')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Sales')
plt.legend()
plt.grid(True)
plt.show()

```

```python
print('Feture')
for year, sales in zip(futureYear, averageFutureSales):
    print(f'Predicted Sales for {year}: {sales:.2f}')

# 计算增长率

global_growth_ratesF      = calculate_growth_rate(predictedGlobalSales[1:])
china_growth_ratesF       = calculate_growth_rate(predictedChinaSales[1:])
netherlands_growth_ratesF = calculate_growth_rate(predictedNetherlandsSales[1:])
spain_growth_ratesF       = calculate_growth_rate(predictedSpainSales[1:])
portugal_growth_ratesF    = calculate_growth_rate(predictedPortugalSales[1:])
germany_growth_ratesF     = calculate_growth_rate(predictedGermanySales[1:])
norway_growth_ratesF      = calculate_growth_rate(predictedNorwaySales[1:])
sweden_growth_ratesF      = calculate_growth_rate(predictedSwedenSales[1:])
france_growth_ratesF      = calculate_growth_rate(predictedFranceSales[1:])

# 全球
plt.figure(figsize=(12, 6))
plt.plot(futureYear[2:], global_growth_ratesF, label='Global')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Growth Rate')
plt.legend()
plt.grid(True)
plt.show()

print('Global Growth')
for year, growth in zip(futureYear[2:], global_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')

# 中国
plt.figure(figsize=(12, 6))
```

```python
plt.plot(futureYear[2:], china_growth_ratesF, label='China')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Growth Rate')
plt.legend()
plt.grid(True)
plt.show()

print('China Growth')
for year, growth in zip(futureYear[2:], china_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')

# 欧盟各国
plt.figure(figsize=(12, 6))
plt.plot(futureYear[2:], netherlands_growth_ratesF, label='Netherlands')
plt.plot(futureYear[2:], spain_growth_ratesF, label='Spain')
plt.plot(futureYear[2:], portugal_growth_ratesF, label='Portugal')
plt.plot(futureYear[2:], germany_growth_ratesF, label='Germany')
plt.plot(futureYear[2:], norway_growth_ratesF, label='Norway')
plt.plot(futureYear[2:], sweden_growth_ratesF, label='Sweden')
plt.plot(futureYear[2:], france_growth_ratesF, label='France')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Growth Rate')
plt.legend()
plt.grid(True)
plt.show()

print('Netherlands Growth')
for year, growth in zip(futureYear[2:], netherlands_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
print('Spain Growth')
for year, growth in zip(futureYear[2:], spain_growth_ratesF):
```

```
    print(f'Growth Rate for {year}: {growth:.2f}')
print('Portugal Growth')
for year, growth in zip(futureYear[2:], portugal_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
print('Germany Growth')
for year, growth in zip(futureYear[2:], germany_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
print('Norway Growth')
for year, growth in zip(futureYear[2:], norway_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
print('Sweden Growth')
for year, growth in zip(futureYear[2:], sweden_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
print('France Growth')
for year, growth in zip(futureYear[2:], france_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')

# 欧盟平均
average_growth_ratesF = np.mean([netherlands_growth_ratesF, spain_growth_ratesF, portugal_growth_ratesF, germany_growth_ratesF, norway_growth_ratesF, sweden_growth_ratesF, france_growth_ratesF], axis=0)
plt.figure(figsize=(12, 6))
plt.plot(futureYear[2:], average_growth_ratesF, label='Average')
plt.title('Linear Regression Model and Prediction')
plt.xlabel('Year')
plt.ylabel('Growth Rate')
plt.legend()
plt.grid(True)
plt.show()

print('Average Growth')
for year, growth in zip(futureYear[2:], average_growth_ratesF):
    print(f'Growth Rate for {year}: {growth:.2f}')
```

Question 5 code:

```
import math
```

```python

import pandas as pd
import matplotlib.pyplot as plt

def createData():

    data = {

        'Year' : [2015, 2016, 2017, 2018, 2019, 2020],
        'MotorVehiclesOwnership' : [279000000, 295000000, 310000000, 327000000, 348000000, 372000000],
        'NEEVsOwnership' : [420000, 910000, 1530000, 2610000, 3810000, 4920000],
        'PureElectricVehicleOwnership' : [330000, 730000, 1250000, 2110000, 3100000, 4000000],
        'CO2Emissions' : [9171.28, 9014.64, 9270.28, 9610.70, 9933.69, 10130.87],
        'CO2EmissionsGDP' : [0.55, 0.53, 0.51, 0.49, 0.46, 0.45],
        'NationalEmissionsOfFourPollutants' : [0.27, 0.26, 0.25, 0.26, 0.24, 0.22],
        'Population' : [358247976, 368117713, 378089414, 388398439, 398976116, 409712858]
    }

    df = pd.DataFrame(data)
    df.set_index('Year', inplace = True)

    return df

def plotOriginalData(data):

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

    plt.subplot(3, 3, 1)
    plt.plot(data.index, data['MotorVehiclesOwnership'], marker='o')
    plt.title('Motor Vehicles Ownership')

    plt.subplot(3, 3, 2)
    plt.plot(data.index, data['NEEVsOwnership'], marker='o', color='orange')
    plt.title('NEEVs Ownership')

```

```
    plt.subplot(3, 3, 3)
    plt.plot(data.index, data['PureElectricVehicleOwnership'], marker='o', color='green')
    plt.title('Pure Electric Vehicle Ownership')

    plt.subplot(3, 3, 4)
    plt.plot(data.index, data['CO2Emissions'], marker='o', color='red')
    plt.title('CO2 Emissions')

    plt.subplot(3, 3, 5)
    plt.plot(data.index, data['CO2EmissionsGDP'], marker='o', color='red')
    plt.title('CO2 Emissions per Unit GDP')

    plt.subplot(3, 3, 6)
    plt.plot(data.index, data['NationalEmissionsOfFourPollutants'], marker='o', color='red')
    plt.title('Total National Emissions Of Four Pollutants')

    plt.subplot(3, 3, 7)
    plt.plot(data.index, data['Population'], marker='o', color='red')
    plt.title('Population')

    plt.tight_layout()
    plt.show()

    return 0

def per100(data):

    MotorVehicles_100     = [math.ceil(d['MotorVehiclesOwnership']          / d['Population'] * 1000000) for i, d in data.iterrows()]
    NEEVs_100   = [math.ceil(d['NEEVsOwnership']   / d['Population'] * 1000000) for i, d in data.iterrows()]
    PureElectricVehicle_100 = [math.ceil(d['PureElectricVehicleOwnership'] / d['Population'] * 1000000) for i, d in data.iterrows()]

    for i in range(len(MotorVehicles_100)):

        NEEVs_100[i]  /= MotorVehicles_100[i]
```

```
        PureElectricVehicle_100[i] /= MotorVehicles_100[i]

        MotorVehicles_100[i]     /= MotorVehicles_100[i]

    CO2EmissionsGDP      = data['CO2EmissionsGDP']
    NationalEmissionsOfFourPollutants= data['NationalEmissionsOfFourPollutants']

    CO2_100 = [d['CO2Emissions'] / d['Population'] * 1000000 for i, d in data.iterrows()]

    plt.figure()

    plt.plot(NEEVs_100, label='NEEVs')
    plt.plot(PureElectricVehicle_100, label='PureElectricVehicle')

    plt.legend()
    plt.title('Comparison of the growth rate of new energy vehicles and pollutant emissions')

    plt.figure()

    plt.plot(CO2EmissionsGDP, label='CO2EmissionsGDP')
    plt.plot(NationalEmissionsOfFourPollutants, label='NationalEmissionsOfFourPollutants')

    plt.legend()
    plt.title('Comparison of the growth rate of new energy vehicles and pollutant emissions')

    plt.show()

    print('单位 CO2')
    print(DanWeiCO2)

    print('全国四项')
    print(QuanGuoSiXiang)

    print('CO2 排放量 / 个人')
    print(CO2_100)

    return 0

```

```
if __name__ == '__main__':

    Data = createData()

    plotOriginalData(Data)

    per100(Data)
```

Question 1 Original datasets:

Year	Sales(Ten Thousand Units)	NEEVs Ownership (Ten Thousand Units)	Sales Production Ratio	Number of Charging Piles (Ten Thousand Units)	Average Price (Ten Thousand RMB)	Charging Cost (RMB/kWh)	Energy Efficiency (km/kWh)
2013	1.76	3	1.005714	2.2	35	1.2	4.2
2014	7.5	12	0.862069	3	32	1.1	4.5
2015	33.1	42	0.873351	4.9	29	1	4.8
2016	50.7	91	0.980658	20	26	0.9	5.1
2017	77.7	153	0.978589	52	23	0.8	5.4
2018	125.6	261	0.988976	80	21	0.7	5.7
2019	120.6	381	0.971014	130	19	0.6	6
2020	136.7	492	1.000732	168	17	0.5	6.3
2021	155.1	784	0.991054	261.7	15	0.4	6.6
2022	247.8	1310	0.990012	370	13	0.4	6.9

Data Source: National Bureau of Statistics, Ministry of Industry and Information Technology, China Association of Automobile Manufacturers, National Development and Reform

Normalized Data

Year	Sales(Ten Thousand Units)	NEEVs Ownership (Ten Thousand Units)	Sales Production Ratio	Number of Charging Piles (Ten Thousand Units)	Average Price (Ten Thousand RMB)	Charging Cost (RMB/kWh)	Energy Efficiency (km/kWh)
2013	0.018399	0.008501	1.043037	0.02015	1.521739	1.578947	0.756757
2014	0.078406	0.034004	0.894061	0.027478	1.391304	1.447368	0.810811
2015	0.346032	0.119014	0.905762	0.04488	1.26087	1.315789	0.864865
2016	0.530024	0.257863	1.017051	0.183184	1.130435	1.184211	0.918919
2017	0.812286	0.433551	1.014905	0.476278	1	1.052632	0.972973
2018	1.313038	0.739586	1.025678	0.732735	0.913043	0.921053	1.027027
2019	1.260768	1.079626	1.007049	1.190694	0.826087	0.789474	1.081081
2020	1.429079	1.394163	1.03787	1.538743	0.73913	0.657895	1.135135
2021	1.621435	2.221593	1.027833	2.396959	0.652174	0.526316	1.189189
2022	2.590533	3.7121	1.026752	3.388899	0.565217	0.526316	1.243243

Question 2 Original datasets:

Year	Number of NEE\	Market Size ('	Industry Chai	Number Of NEE'	Market Shar	Market Pen	Productior	Sales (Ter	NEEVs Owners	Average Price	'Government :	Charging Co:	Number Of Charging Piles (Hundred Thousand Units)
2013	300	5	230	2024	0.9	0.1	1.75	1.76	3	35	30	1.2	2.2
2014	500	15	280	3111	1.3	0.4	8.7	7.5	12	32	50	1.1	3
2015	800	50	320	4566	2.5	1.3	37.9	33.1	42	29	70	1	4.9
2016	1200	120	370	8205	3.1	1.8	51.7	50.7	91	26	100	0.9	20
2017	1500	250	420	12262	5.3	2.6	79.4	77.7	153	23	120	0.8	52
2018	1800	400	460	17647	7.2	3.6	127	125.6	261	21	140	0.7	80
2019	2000	600	500	18498	9.7	4.7	124.2	120.6	381	19	160	0.6	130
2020	2200	800	550	19739	11.4	5.7	136.6	136.7	492	17	180	0.5	168
2021	2400	1000	590	21300	13.4	6.4	156.5	155.1	784	15	200	0.4	261.7
2022	2600	1200	630	24700	25.6	7.3	250.3	247.8	1310	13	220	0.4	370

data source:
the National Bureau of Statistics, the Ministry of Industry and Information Technology, the China Association of Automobile Manufacturers,
the National Development and Reform Commission of the People's Republic of China, and the Forward-looking Industry Research Institute of EVCIPA.

Question 3 Original datasets:

Year	Global Traditional Car sales	NEEVs Market Share	NEEVs Market Penetration	New Car Production	New Car sales	Effective Patent of car industry(China)	Patent Count	Global Power Demand	India Power Demand	China Power Demand	US Power Demand	Eruope Power Demand
2010								1100.00		330.00	190.00	210.00
2011	5784.00							2200.00		2400.00	130.00	160.00
2012	6093.64							4500.00		800.00	600.00	480.00
2013	6342.92	0.9	0.1	1.75	1.76	11605.00	2024	5900.00		1800.00	540.00	420.00
2014	6570.82	1.3	0.4	8.7	7.5	14106.00	3111	4500.00		1500.00	1600.00	1100.00
2015	6631.42	2.5	1.3	37.9	33.1	18840.00	4566	6200.00		3300.00	1900.00	830.00
2016	6946.44	3.1	1.8	51.7	50.7	23194.00	8205	18000.00		2700.00	7000.00	2100.00
2017	7069.48	5.3	2.6	79.4	77.7	34481.00	12262	11000.00		7900.00	3700.00	1300.00
2018	6869.05	7.2	3.6	127	125.6	45168.00	17647	30000.00		6500.00	10000.00	1800.00
2019	6403.35	9.7	4.7	124.2	120.6	57360.00	18498	21000.00	0.01	20000.00	6300.00	5400.00
2020	5391.59	11.4	5.7	136.6	136.7	62403.00	19739	24000.00	0.05	13000.00	5400.00	3900.00
2021	5643.78	13.4	6.4	156.5	155.1	71478.00	21300	34000.00	0.12	22000.00	6500.00	4000.00
2022	5748.54	25.6	7.3	250.3	247.8	80855.00	24700	65000.00	210.00	25000.00	15000.00	19000.00

Data Sourc Data Source: IEA

Question 4 Original datasets:

Year	Market Share	Production(Ten Thousand Vehicles)	Car Sales（Ten Thousand vehicles）	Effective Patent
2013	0.9	1.75	1.76	
2014	1.3	8.7	7.5	14106.00
2015	2.5	37.9	33.1	18840.00
2016	3.1	51.7	50.7	23194.00
2017	5.3	79.4	77.7	34481.00
2018	7.2	127	125.6	45168.00
2019	9.7	124.2	120.6	57360.00
2020	11.4	136.6	136.7	62403.00
2021	13.4	156.5	155.1	71478.00
2022	25.6	250.3	247.8	80855.00

Data sources: National Bureau of Statistics, Ministry of Industry and Information Technology, China Association of New Energy Vehicles, National Development and Reform Commission of the People's Republic of China, EVCIPA Prospective Industry Research Institute.

Product	Registration Time	Investigation Duration (months)	Punitive Tax Rate for Non-responding Enterprises (%)
Minibus Tires	2017/8/11	14.6	61.76
Steel Hubs	2019/2/15	12.8	66.4
Fiberglass	2019/2/21	13.7	99.7
Polyvinyl Alcohol	2019/7/30	14.2	72.9
Hot-rolled Stainless Steel	2019/8/12	14.1	19
Aluminum Profiles	2020/8/14	14.1	24.6
Optical Fiber Cable	2020/9/24	14	44
Wind Tower	2020/10/21	14	19.2
Aluminum Conversion Foil	2020/10/22	13.7	28.5
Steel Fasteners	2020/12/21	14.1	86.5
Graphite Electrode	2021/2/17	13.8	74.9
Silicon Calcium Alloy	2021/2/18	13.3	50.7
Stainless Steel Drum	2022/5/13	13.9	69.6
Data Source: https://user.guancha.cn/main/content?id=1054983			

Year	Effective Patent	Total Car Industry Patent Count	China: Car Industry Patent Count	BiYaDi Company Patent Count	Foton Motor Company Patent Count	ChangAn Automobile Company Patent Count	Haima Automobile Company Patent Count	ZoTye Auto Company Patent Count
2012	11605.00	7476.00	31297.00	9833.00	2166.00	4974.00	2.00	19.00
2013	14106.00	9041.00	38237.00	11277.00	3347.00	5573.00	2.00	20.00
2014	18840.00	11722.00	44284.00	12506.00	4719.00	6419.00	3.00	25.00
2015	23194.00	12840.00	46820.00	13981.00	6864.00	7134.00	4.00	25.00
2016	34481.00	15367.00	53133.00	15525.00	8024.00	8503.00	4.00	29.00
2017	45168.00	16701.00	58579.00	17840.00	9731.00	9768.00	4.00	38.00
2018	57360.00	19678.00	66367.00	21090.00	10579.00	11262.00	4.00	38.00
2019	62403.00	19955.00	70247.00	24875.00	11249.00	12413.00	4.00	38.00
2020	71478.00	22676.00	75576.00	29777.00	12063.00	13681.00	4.00	38.00
2021	80855.00	26988.00	86386.00					
Data Source:National Bureau of Statistics, National Intellectual Property Administration								

Question 5 Original datasets:

Year	Number of Motor Vehicles (units)	Number of New Energy Vehicles (units)	Number of Pure Electric Vehicles (units)	China: CO2 Emissions	Japan: CO2 Emissions	South Korea: CO2 Emissions	Vietnam: CO2 Emissions	India: CO2 Emissions	USA: CO2 Emissions
2011				8793.49	1207.47	613.71	132.11	1706.36	5336.16
2012				8977.56	1293.80	612.61	129.28	1825.46	5089.15
2013				9214.09	1282.22	619.99	134.00	1892.62	5246.61
2014	24577.2万			9235.53	1248.66	615.01	150.20	2042.08	5251.66
2015	2.79亿	42万	33万	9171.28	1209.14	622.78	181.94	2109.83	5137.48
2016	2.95亿	91万	73万	9014.64	1189.19	633.17	197.35	2207.23	5038.00
2017	3.10亿	153万	125万	9270.28	1182.65	641.83	199.04	2283.81	4978.76
2018	3.27亿	261万	211万	9610.70	1161.51	659.11	240.36	2381.66	5133.22
2019	3.48亿	381万	310万	9933.69	1120.61	635.32	291.09	2407.27	4981.55
2020	3.72 亿	492.0 万	400万	10130.87	1031.81	588.12	285.02	2237.47	4462.66
2021	3.95亿	784万	640万	10563.47	1066.64	602.98	273.15	2464.71	4768.38
2022	4.17亿	1310万	1045万	10550.25	1065.71	592.40	270.03	2595.85	4825.78
2023（至9月底）	4.3亿	1821万	1401万						

Data Source：Wind,BP,World Bank

Year	China CO2 Emissions per GDP unit	Japan CO2 Emissions per GDP unit	South Korea CO2 Emissions per GDP unit	Vietnam CO2 Emissions per GDP unit	India CO2 Emissions per GDP unit	USA CO2 Emissions per GDP unit	National Total Emissions of Four Pollutants (ten thousand tons)	Carbon Monoxide	Hydrocarbon Oxides	Hydrocarbon Oxides	Particulate Matter
2011	0.67	0.26	0.37	0.30	0.31	0.31					
2012	0.63	0.26	0.36	0.27	0.31	0.29					
2013	0.62	0.25	0.35	0.27	0.30	0.29					
2014	0.59	0.24	0.33	0.27	0.32	0.29	4547.3	3433.7	428.4	627.8	57.4
2015	0.55	0.23	0.31	0.29	0.30	0.27	4532.2	3461.1	430.2	584.9	56
2016	0.53	0.23	0.30	0.29	0.28	0.26	4472.5	3419.3	422	577.8	53.4
2017	0.51	0.22	0.30	0.27	0.28	0.25	4359.7	3327.3	407.1	574.3	50.9
2018	0.49	0.21	0.28	0.31	0.27	0.26	4065.3	3089.4	368.8	562.9	44.2
2019	0.46	0.20	0.27	0.33	0.25	0.24	1603.8	771.6	189.2	635.6	7.4
2020	0.45	0.19	0.25	0.33	0.24	0.22	1593	767.7	190.2	626.3	6.8
2021							1557.7	768.3	200.4	582.1	6.9
2022											