Team Number	apmcm2301268
Problem Chosen	C

Analysis and Prediction of New Energy Electric Vehicles (NEEVs) in China

Abstract

China has witnessed remarkable advancements in the field of NEEVs. This article used various methods to analyze and predict NEEVs development in China.

For problem 1, we developed a **3-level Analytic Hierarchy Process(AHP)** evaluation model to quantitatively analyze the factors influencing the development of NEEVs in China. First, we identified 29 factors. To ensure a systematic and hierarchical analysis of these factors, we categorized them into different groups based on **SWOT** and **PEST** analytical approach. Then, consulting references and industry development reports, we constructed judgment matrices for each layer. Finally, we derived weights for each factor and obtained the **top five influential factors**.

For problem 2, we employ **grey forecasting model** to predict the sales of NEEVs for the next 10 years. Observing the trend, we deduce an exponential relationship between sales and time. By applying **Critic Method** on the top 5 weights, we construct the NEEVs development index and perform **Spearman correlation test** with logarithmic sales,validating our hypothesis. Considering that exponential growth is not sustainable indefinitely, we propose **optimized hyperbolic tangent function** to accurately capture the nonlinear association between sales and time. Lastly, our prediction indicates that China's NEEVs sales will reach **48.83 million by 2032**.

For problem 3, through an analysis of the respective sales fluctuations and market share dynamics of NEEVs, in conjunction with the epidemic and macroeconomic policies, our findings suggest that NEEVs will have an increasing impact on the **reduction of sales of traditional energy vehicles**.

For problem 4, we conducted an analysis on the timing of policy implementation in other countries aimed at curbing China's rapid development of NEEVs. Employing a **Comparative Analysis Based on Control**, we examined the impact of intervention policies on overseas sales of NEEVs. Our findings indicate that policies implemented by other countries have **limited effectiveness in restraining China's NEEVs growth**.

For problem 5, we selected carbon and SO2 emissions as indicators to assess the ecological impact of NEEVs. We developed the **Analysis of Electric Vehicle's Ecological Impact (AEVE)** model. The calculation results demonstrate that in a city with a population of 1 million, NEEVs can effectively replace conventional energy vehicles, resulting in **a reduction of 84.78% in carbon emissions**; however, it is worth mentioning that this transition may lead to **an increase in SO2 emissions**.

Lastly, we drafted an open letter to disseminate the merits of NEEVs and highlight the contributions made by diverse nations.

Keywords: 3-level AHP ; SWOT ; PEST ; grey forecasting model ; optimized hyperbolic tangent function ; Spearman correlation analysis ; AEVE model ; Multivariate linear model

Contents

1 Introduction

1.1 Problem Background

New energy vehicle(NEV) is an automobile with advanced technical principles, new technology and new structure formed by using non-conventional automotive fuels and synthesizing advanced technologies in power control and drive. Among all types of new energy vehicles, new energy electric vehicles have seen the most prominent development in the last few years and are widely welcomed by consumers worldwide.

Compared with traditional gasoline and diesel vehicles, new energy vehicles are usually considered to be an environmentally-friendly alternative. Studying the development of new energy vehicles is of great significance to the construction of ecological civilization, environmental protection and sustainable urban development.

1.2 Problem Restatement

Considering the background information, we need to solve the following problems:

- **For problem 1:** Select representative indicators and collect relevant data. Establish an evaluation model to describe the impact of these indicators on the development of new energy electric vehicles in China.
- **For problem 2:** Select indicators and collect relevant data on the past development of new energy electric vehicles in China. Establish a prediction model to forecast theirs development over the next 10 years.
- **For problem 3:** Select representative indicators and collect relevant data. Establish an evaluation model to describe the impact of new energy electric vehicles on the global traditional energy vehicle industry.
- **For problem 4:** Access the policies of other countries regarding resistance to new energy electric vehicles in China. Select indicators and collect data to establish an evaluation model that analyzes the effects of these policies on the development of new energy electric vehicles in China.
- **For problem 5:** Select representative indicators and collect relevant data, establish an evaluation model to analyze the impact of the electrification of new energy electric vehicles in cities on the ecological environment.
- **For problem 6:** Based on the finding from problem 5, write an open letter to the citizens to raise awareness about the benefits of new energy electric vehicles and the contributions of the electric vehicle industry in various countries around the world.

1.3 Literature Review

As an effective technology to reduce traffic pollution emissions, the new energy vehicle(NEV) industry has developed rapidly in recent years, especially in China. Many scholars have made contributions to the research of the development trend of NEVs.

Published by the International Energy Agency (IEA),Global EV Outlook 2022Securing supplies for an electric future[1] and Global EV Outlook 2023 Catching up with climate ambitions[2] provides an overview of the market for electric vehicles (EVs) around the world. It also includes projections for the future of the EV market based on different scenarios and provides recommendations for policymakers and stakeholders to support the transition to electric mobility. In domestic, Yu, K., Li, S., Shi & Y provides an overview of the policies, market size, and development trends of new energy vehicles in China[3].Zongwei Liu et al. described critical issues of energy efficient and new energy vehicles development in China[4].All of them give much enlightment on factors selection. As for the prediction of the development of NEVs, various models have been leveraged and employed. Jensen et al. proposed an approach combining special selection model and diffusion model to predict the market share of NEVs[5];Lianyi Liu et al. forecast the development trend of new energy vehicles in China by an optimized fractional discrete grey power model[6].

The impact of NEVs on the ecological environment is another hot research field.Ya Wu and Li Zhang mainly studied the development of NEVs reduce the emission of air pollutants and greenhouse gases in developing countries[7]. Using case study research method, Nan Li et al. analyse potential impacts of electric vehicles on air quality in Taiwan[8].

Although there are already many models to assess the development of NEVs in China and many approaches to forcast the development of NEVs as well as the impact of NEVs on the ecological environment, there is no integration particularly for NEVs in China including evaluation, prediction and impact analyse in a concise and clear way. Besides, as another Chinese symbol, it is necessary for us to better understand the development trend of NEVs in China to keep pace with the times and better publicize the benefits of NEVs to the citizens. Therefore, it is crucial to build a model to analyze , measure and assess the development trend of NEVs in China.

2 Assumptions and Justifications

- **Assumption 1:** All the data given is true and reliable.

  Justification: We collect information based on a number of authoritative databases with guaranteed data sources, which provides a good foundation for our model.

- **Assumption 2:** No major emergencies will occur during the predicted period.

  Justification: Major emergencies tend to be rare and are therefore not considered. In normal situations the indicators used are consistent with the expected pattern of development.

- **Assumption 3:** The policies we've been informed about at both domestic and foreign are true.

Justification: Policies that have been released are effective and have been truly implemented, only then can we have a basis for studying the policy's impact on new energy vehicle sales.

3 Notations

Table 1: Notations Table

Notations	Definition
$y_{chi}(t)$	annual sales of new energy vehicles in China
$y_{glo}(t)$	annual sales of new energy vehicles globally
$z_{glo}(t)$	annual sales of traditional energy vehicles globally
v_{ahpi}	weights of indicator i obtained through AHP
v_{crii}	weights of indicator i obtained through critical method
v_i	weights of indicator i obtained by comprehensively combining v_{ahpi} and v_{crii}
$score(t)$	score reflecting annual new energy vehicle development in China
x_{it}	score of indicator i in year t

4 Solution to Problem 1

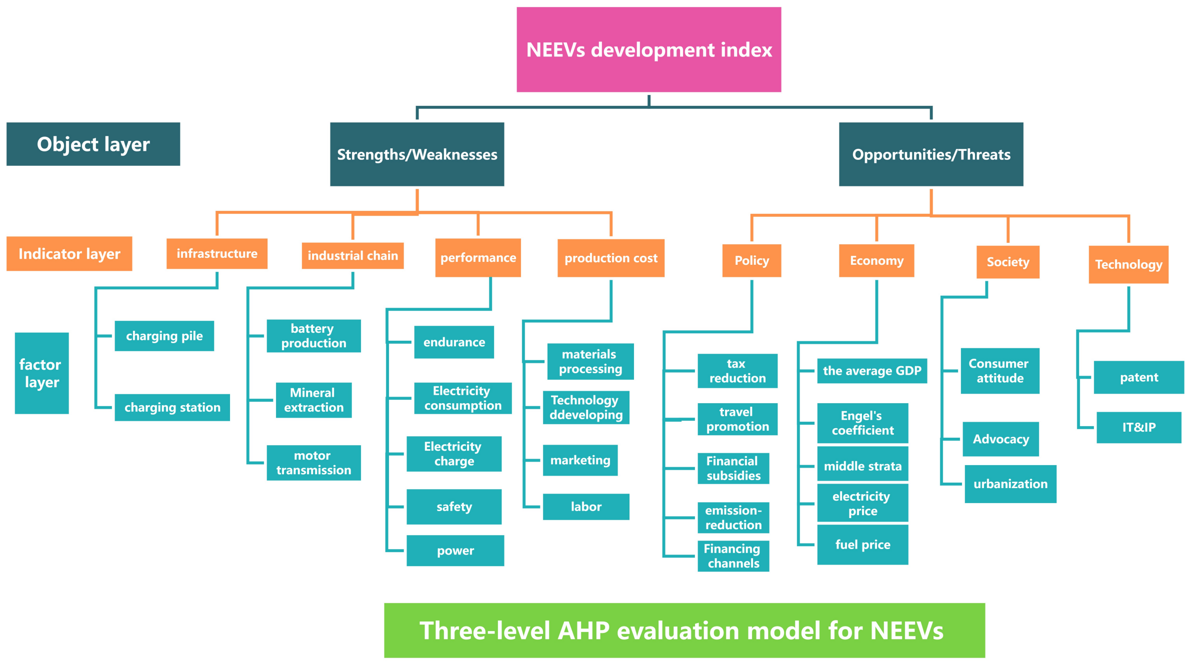
To describe the impact of main factors on the development of new energy electric vehicles in China, an evaluation model based on Analytic Hierarchy Process(AHP) was established in this section. AHP is a comprehensive evaluation method that transforms subjective judgment to the comparison of importance between two-by-two elements and quantify fuzzy problems by establishing a recursive hierarchy.

4.1 Indicator selection and Index system

First of all, we consider what aspects we choose to select indicators. To comprehensively analyze the industry's current status and future prospects, it is imperative to conduct an assessment of both the internal and external environments. The analysis of the internal environment of an industry is a fundamental step in understanding the industry's strengths and weaknesses. Simultaneously, analyzing the external environment of the industry is equally importance as it allows for the evaluation of opportunities and threats that the sector faces. By combining the analysis of the internal and external environments, we can obtain the main factors from both aspects in a more comprehensive way.

Therefore, in this process we utilize the SWOT analysis to select indicators from internal and external environment of the industry. SWOT analysis is a comprehensive analysis method to evaluate the current situation and prospects of an industry by combining its internal strengths and weaknesses, as well as its external threats and opportunities. Moreover, for the extra-industrial environment, we apply the PEST analysis, in other word, indicators are selected from four aspects: policy, economy, society and technology. PEST analysis focuses on the impact of the external environment, while SWOT analysis considers both internal and external factors. Therefore, PEST analysis and SWOT analysis can be combined for a comprehensive analysis to avoid ignoring internal factors and oversimplifying the environment.

The index system established in this problem has a top target (The weights of indicators for the development of new energy vehicle in China) and two aspects (the Intra-industry Environment and the Extra-industrial Environment). Each aspects is made up of three layers, which are the object layer(O), and the indicator layer(I) and the factor layer(F).



4.2 The Intra-industry Environment

First we analyze the indicators of Intra-industry Environment and their weights. Through referring to relevant information, we know that the indicators affecting the internal environment of the industry include infrastructure(INF), industrial chain(IC), vehicle performance(VP) and vehicle production cost(VPC).

By comparing each pairs of indicators, we obtain the judgment matrix. The value of corresponding position within the matrix is the comparison result expressed in the importance scale value 1–9 (and its reciprocal). Then we use the root square method to solve the eigenvalue and eigenvector of the matrix. The resulting eigenvector is the weight of each factor. In addition, to determine the reliability of the weights obtained in the judgment matrix, it is necessary to perform a consistency test and calculate the consistency ratio CR. If CR < 0.1, it means the judgment matrix passes consistency test; if CR ≥ 0.1, we need to modify our judgment matrices. The equation of it is:

$$CR = \frac{CI}{RI} \tag{1}$$

RI is the deviation from the full consistency indicator and CI is the average stochastic consistency indicator obtained from the formula following, where λ is eigenvalue of the judgment matrix and n is its order :

$$CI = \frac{\lambda - n}{n - 1} \tag{2}$$

We calculate the eigenvalue of the O-I matrix and the result is recorded as λ_1. The eigenvector obtained is

$$\omega_1 = (0.47921725, 0.21941554, 0.17907751, 0.12228969) \tag{3}$$

So the weights of INF, IC, VP, and VPC can be approximated as 0.48, 0.22, 0.18, and 0.12. The judgment matrix passes consistency test with CR =0.0215 < 0.1.

With relevant information, we learn that each indicator is influenced by several factors. And it is these specific influencers that are the main factors required by this problem. Therefore we have to analyze the weights of various factors under each indicator. Applying the same method, we can create several I-F matrices, each of which reflects the relative importance of the factors under one indicator. For these matrices we calculate their eigenvalues and eigenvectors, and make consistency test for these matrices to finally determine the weights of different factors in the corresponding indicators. The data we obtained are shown in the table below:

Table 2: The data from I-F matrix of the Intra-industry Environment

Indicator	Factor	Weight
infrastructure	charging pile	0.30
	charging station	0.70
industrial chain	battery production industy	0.66
	mineral extraction industy	0.18
	motor transmission system	0.16
vehicle performance	endurance	0.39
	electricity comsumption	0.10
	electricity charge	0.19
	safety	0.19
	power	0.13
vehicle production cost	materials processing cost	0.11
	technology developing cost	0.59
	marketing cost	0.15
	labor cost	0.15

4.3 The Extra-industrial Environment

Then we analyze the indicators of Extra-industrial Environment and their weights. The indicators affecting the external environment of the industry include policy(P), economy(E), society(S) and technology(T). Similarly, we calculate the eigenvalue of the O-I matrix of this aspect, the Extra-industrial Environment. The result is recorded as λ_2. The eigenvector obtained is

$$\omega_2 = (0.4640644, 0.15402582, 0.15402582, 0.22788396) \tag{4}$$

So the weights of P, E, S, T can be approximated as 0.46, 0.15, 0.15, 0.24 and the judgment matrix passes consistency test with CR = -0.1938 $<$ 0.1. In addition, the I-F matrices under each indicators are also obtained and the data acquired from the I-F matrices are shown in the table below:

Table 3: The data from I-F matrix of the Extra-industry Environment

Indicator	Factor	Weight
policy	incentive policy	0.49
	purchase and travel promotion	0.16
	financial subsidies	0.17
	energy-saving and emission-reduction assessment in various regions	0.10
	financing channels and listing support	0.08
economy	GDP per capita	0.49
	Engel's coefficient	0.22
	middle society strata percentage	0.13
	electricity price	0.08
	fuel price	0.08
society	consumer attitude	0.43
	advocacy	0.33
	urbanization development process	0.24
technology	patent	0.42
	intelligent transportation and Internet application	0.58

4.4 Factors and Impact Values

After constructing the hierarchical structure of each of the two aspects, we also need to assign a value to the influence of two aspects on the top target. By reviewing the relevant information, we learn that the internal environment has a greater impact than the external environment. So we set the total value as 100 for the development of China's new energy vehicle industry and assign a value of 60 to the Intra-industrial Environment and 40 to the Extra-industrial Environment.

Synthesizing the above analysis we finally got the impact value of each factors. The larger the value, the more weight that factor has on the development of China's new energy vehicle industry. All the impact value corresponding to each specific factors are as follow:

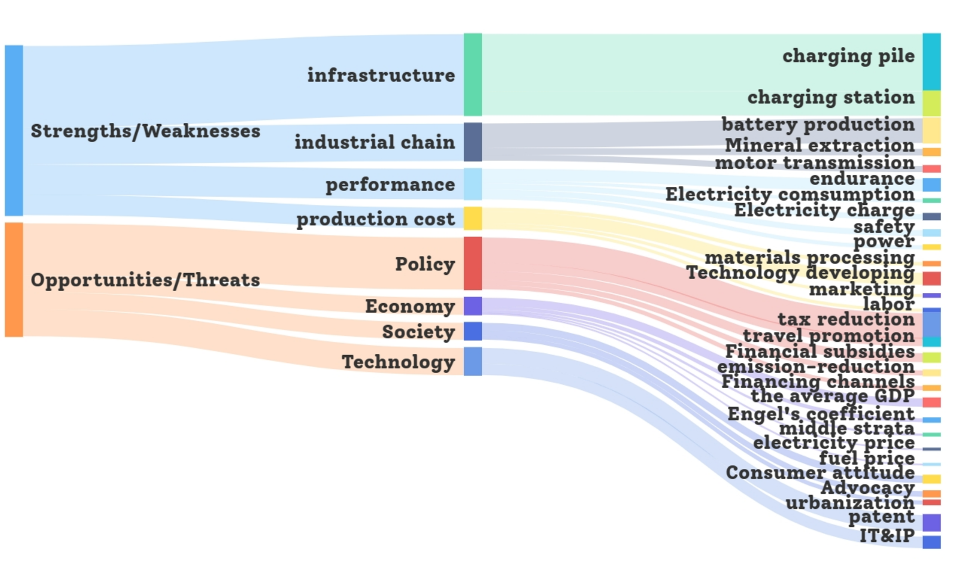


Figure 1: The influence of factors

From the figure above, the top five factors with the highest impact value are shown:

- **charging pile(CP)**

  Reason Charging piles are charging devices that provide energy supplementation for electric vehicles. Equally as an important representative of infrastructure construction, charging piles are different from charging stations because they can be widely distributed in places other than charging stations, such as parking lots. Therefore, it has a very obvious convenience, which greatly influences users' willingness to purchase new energy vehicles.

- **incentive policy(IP)**

  Reason The incentive policies implemented by the government play a key role in the sales of NEEVs and its development. The main representative of incentive policies in China is the abolition of the purchase tax, which appeared in 2014 and was extended three times in 2017, 2020, and 2022, greatly reducing the purchase cost. In addition, the Chinese government provides subsidies to manufacturers of NEEVs, which leads to lower production costs and further stimulates the growth of the industry.

- **battery production industry(BPI)**

  Reason Batteries are a core component of NEEVs and their performance, cost and availability directly affect the range, safety and cost-effectiveness of NEEVs. China is actively developing its battery production industry to improve battery technology and reduce costs, thereby boosting the development of the industry.

- charging station(CS)

  Reason The number and distribution density of charging stations have a direct impact on the ability to travel long distances and the convenience of charging. The charging speed and service quality of charging stations also have an impact on users' charging experience and vehicle purchase decision.

- patent(PT)

  Reason Patents play a role in protecting innovation and promoting technological progress in the industry. Enterprises with core technologies and patents can take an advantageous position in technological competition and promote the innovation and development of the NEEVs industry.

5 Solution to Problem 2

Problem 2 requires us to analyze the development of China's new energy electric vehicle industry, so we need to identify a set of indicators that can evaluate the relationships between these indicators and the industry's development. However, collecting extensive data can make the model-building process more challenging. Considering that we have already calculated the impact values of all the indicators in Problem 1, we can select the five indicators with the highest impact values and apply to this problem.

5.1 Indicator Selection and Weight Analysis

5.1.1 The Impact Value and the AHP Weight

From the result of problem 1, we obtain the top five factors with the highest impact value from calculations above: charging pile(CP), incentive policy(IP), battery production industry(BPI), charging station(CS), patent(PT).

Among these five indicators, we reassign their weights according to their impact value, with the sum of the weights of these five indicators being 1. Then the AHP weights are obtained.

5.1.2 The Critical Weight

Since AHP weights are are too subjective, we decided to use another method to get objective weights. The critical method is applied in this section to evaluate and assign weights to indicators, determining the most active indicator based on the highest weight. This methodology considers the intensity of comparison between evaluation indicators and the potential conflicts among them, while also considering their correlations. The approach avoids solely relying on larger numerical values to assign greater weight, instead utilizing the intrinsic characteristics of the data to establish an objective and scientifically grounded weighting method.

The first consideration is the comparison intensity, which addresses the disparity between the given index and other evaluation schemes. This involves assessing the variability among different indicators, typically represented by the standard deviation. In simpler terms, indicators with a higher standard deviation, indicating greater fluctuation, are assigned higher weights. The specific calculation for this approach is as follows:

$$\begin{cases} \bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \\ \\ S_j = \sqrt{\frac{\sum_{i=1}^{n}(x_{ij}-\bar{x}_j)^2}{n-1}} \end{cases} \tag{5}$$

Then we deal with the conflict the conflicts among indicators, which can be expressed by the correlation coefficient R_j. The specific equations are as follows:

$$R_j = \sum_{i=1}^{p}(1 - r_{ij}) \tag{6}$$

When two indicators exhibit a strong positive correlation, a smaller conflict indicates a lower weight. In the CRITIC method, when the standard deviation remains constant, a higher degree of positive correlation between two indicators (i.e., a correlation coefficient close to 1) results in the minimum conflict. This implies that the two indicators in the evaluation scheme reflect similar information.

Finally, the amount of information is calculated by multiplying the conflict and variability of the previously determined indicators. It represents the objective proportion of the evaluation indicator subset within the entire evaluation system. A larger value indicates a higher weight, thus exhibiting a positive correlation with the final weight.

$$C_j = S_j \sum_{i=1}^{p}(1 - r_{ij}) = S_j \cdot R_j \tag{7}$$

Finally, we calculate the objective weight as follows:

$$W_j = \frac{C_j}{\sum_{j=1}^{p} C_j} \tag{8}$$

5.1.3 The Comprehensive weight

We take 0.5 times the AHP weight and 0.5 times the CRITICAL weight to get the comprehensive weight. This comprehensive weight can analyze subjective and objective in a reasonable way to evaluate the importance of the indicator. The detail data are as follows:

Table 4: The weight analysis of top five factors

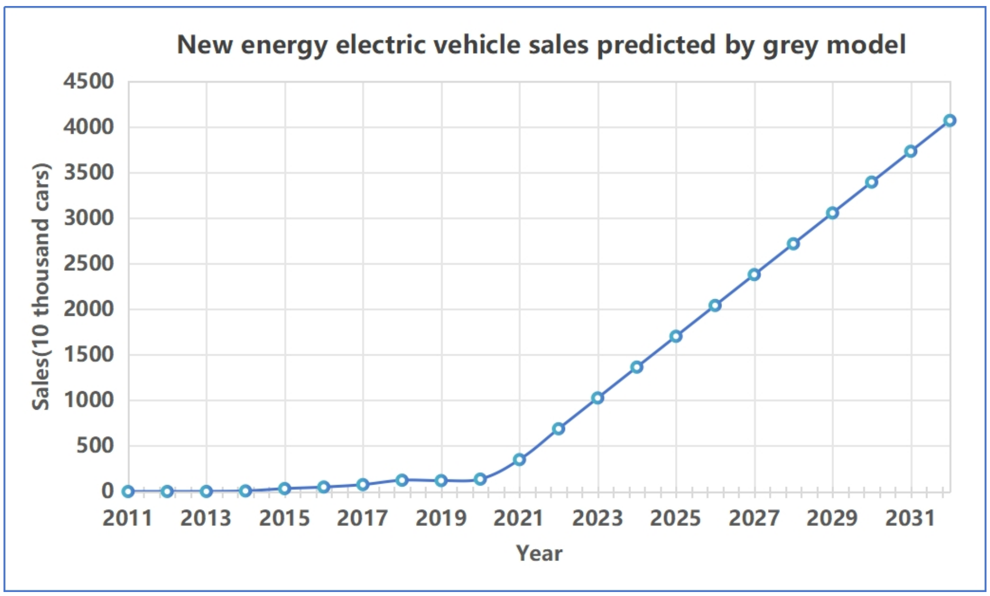
Indicator	Impact Value	AHP Weight	Critical Weight	Comprehensive Weight
charging pile	20.16	0.387	0.337	0.362
incentive policy	9.016	0.173	0.152	0.1625
battery production industry	8.712	0.167	0.165	0.166
charging station	8.64	0.166	0.173	0.1695
patent	5.568	0.107	0.173	0.14

5.2 Initial attempt at modeling based on ARIMA Model

There are many models that can be used to predict industry development. Since industrial development contains time variables, the first model considered is the ARIMA model, the advantage of which can capture time trends and make predictions accordingly. But the model do not handle some of time-series data well. In this process we find that the noise in the data is still obvious after differencing. What's more, there is a dearth of available data information due to the nascent nature of the new energy vehicle industry. Therefore, we abandoned that approach.

5.3 Hypotheses based on Gray Prediction Model

Due to the nascent nature of the NEV industry, there is often a dearth of available data information. The collection of exogenous variables requires substantial time and their reliability significantly impacts the accuracy of modeling outcomes. Consequently, grey prediction model offers distinct advantages in forecasting NEV market trends.Gray prediction model is a method that can be used to make effective predictions for a small number of data series with low data completeness. Consequently, gray prediction models offer distinct advantages in forecasting market trends.Considering the insufficient amount of data, we decided to use gray prediction model.



Using the collected data we get the image obtained by gray prediction model. We hypothesize that there should be exponential growth based on the image.

5.4 Hypothesis testing based on Multiple Linear Regression

In this process we conduct a hypothesis testing to examine the sale of new energy vehicle in China is growing exponentially. In order to facilitate the realization of this goal, we set up a corresponding variable:

$$h(t) = \ln y_{chi}(t) \tag{9}$$

Next, to quantify the relationship between the top five factors we derived from problem 1 and the development of new energy vehicle in China, a multiple linear regression equation is established as follow:

$$score(t) = \sum_{1}^{5} v_i x_{it} \tag{10}$$

Then,we conducted a correlation analysis between h(t) and score(t). Among all the approaches, Spearman correlation coefficient is a method for studying convergence between two sets of variables. It does not require a large sample size, nor does it assume normality of the groups, and it gives good results. Therefore, we use the method of Spearman correlation coefficient for the test. The definition of Spearman correlation coefficient is as follows:

$$\begin{cases} r = l - \frac{6\sum_1^n d_i^2}{n(n^2-1)} \\ \\ t = r\sqrt{\frac{n-2}{1-r^2}} \end{cases} \tag{11}$$

We obtain that $r = 0.9149$, $\rho = 3.037 \times 10^{-5}$, indicating that a significant convergent relationship is shown between h(t) and score(t). Consequently the sale of new energy vehicle in China are consistent with exponential growth. Later, we will calculate its specific exponential function by applying the least squares method, finally having

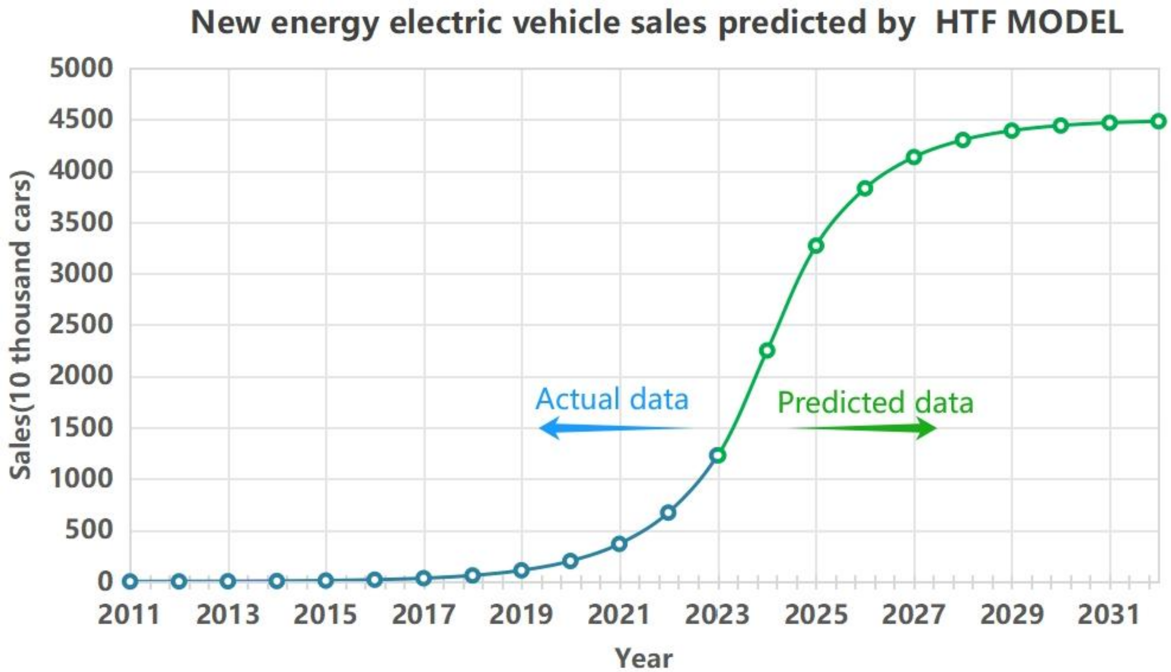
$$y = 0.4738e^{0.6047(t-2010)} \tag{12}$$

5.5 Further adjustments based on the Exponential Function

After obtaining the growth model in the form of an exponential function for the sales of new energy vehicles, we consider that the sales of new energy vehicles cannot keep growing indefinitely wiyh the detail reasons mention below.

Our team suggests that the exponential growth in China's new energy vehicles is due to the elimination of the purchase tax on new energy vehicle purchases, and that the cancellation of subsidies for new energy vehicle purchases in 2023 will have an impact on the development of new energy vehicles in China. Taking two conditions into consideration, namely the gradual development of the Chinese market and its eventual saturation in the future, and the change in national policy, we hypothesize that the development of new energy vehicle sales will change in 2024, lose its exponential growth trend, and then grow at a slowly decreasing rate in the following time, and combining with the historical data curves, our team proposes the following equation for the period after 2024The equation for the subsequent period is roughly satisfied:

$$y = 4500.6 - 0.4738e^{0.6047(2038-x)} \tag{13}$$



Therefore, the sales of new energy vehicles in China in our model satisfy the following segmented function:

$$y = \begin{cases} 0.4738e^{0.6047(t-2010)} & t \leq 2024 \\ \\ 4500.6 - 0.4738e^{0.6047(2038-x)} & t > 2024 \end{cases} \tag{14}$$

6 Solution to Problem 3

We collected global sales of new and traditional energy vehicles from 2011 to 2022. In the figure we can roughly compare the sales volume of new energy vehicles and traditional energy vehicles and their trends. However, we need to analyze the impact of new energy electric vehicles on the global traditional energy vehicle industry, so in order to remove the effect of changes in the vehicle market, we will start with the ratio of the sales volume of the two. Therefore, we consider the sum of the total sales of new energy vehicles and conventional energy vehicles as an aggregate, and study the percentage of sales of both in the total sales.

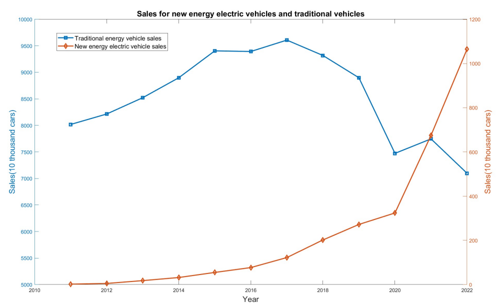


Figure 2: Sales proportion of new energy electric vehicles and traditionhal vehicles

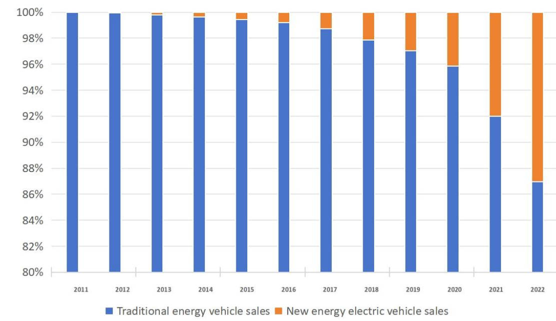


Figure 3: Sales proportion of new energy electric vehicles and traditionhal vehicles

It can be observed that sales of traditional energy vehicles are on the rise until 2017, after which they begin to decline and are lowest in 2020. Combined with the wake of the coronavirus (Covid-19) pandemic, we arrive at the plausibility that car sales are lower in 2020 to 2022 car sales. However, we observe that the sales of new energy vehicles have been rising at an extremely fast pace, and even the epidemic has not curbed the sales of new energy vehicles, which is a good indication that more and more car shoppers are moving toward new energy vehicles rather than traditional energy vehicles. Figure 2 also shows that the sales of new energy vehicles account for a larger and larger proportion, which undoubtedly has a certain impact on the sales of traditional energy vehicles.

7 Solution to Problem 4

This problem asks to analyze the impact of resistance policies from other countries on the development of China's new energy vehicle industry. We choose the export volume of China's new energy vehicles as a reflection indicator. The larger the export volume of China's new energy vehicles, the better the industry is developing on an international scale.

Moreover, in order to analyze the impact of the resistance on the volume of exports, we adopt a control-based comparative analysis to observe the changes in overseas sales of new energy vehicles by controlling for the intervention of the factor ”resistance policy”. For the situation with resistance policy, we can obtain the true export volume of China's new energy vehicles in the past years as the evaluation subject and set it as control group. As for the situation without resistance policy, we use the export volume before the appearance of resistance policy to fit the curve, and the fitted curve will reflect the export volume of China's new energy vehicles in the case that resistance policy never appeared, which is set as treatment group.

7.1 Sample Set and Fitting Curve

We have collected data of China's NEV export volume from 2011 to the present as shown in the following table:

Year	Export volume/ 10,000 units
2011	0.5
2012	1.2
2013	2.3
2014	4.8
2015	6.4
2016	7.6
2017	10.6
2018	14.71
2019	25.4
2020	44.6
2021	59
2022	67.9
2023	220

Through extensive information, the following resistance policies are obtained.

- In 2021, the Federal Coalition for Advanced Batteries (FCAB) released the National Lithium Battery Blueprint 2021-2030, which provides financing for the advanced battery supply chain for electric vehicles in the U.S., which has weakened the competitiveness of China's new energy vehicles in the U.S. to a certain extent.

- In 2022, Biden signed the U.S. IRA bill in August, a comprehensive update on the tax credit policy aspect of new energy vehicles. According to the U.S. Treasury note, a prerequisite for receiving the subsidy is that the final assembly of the new vehicle must be in North America.

- In 2023, the European Union launched a countervailing investigation into China's new energy vehicles, with the underlying aim of significantly raising the cost of China's new energy vehicle exports through the imposition of punitive tariffs, in order to forcefully undermine China's competitiveness in the field.

Overall, the policies that mainly affect the development of China's NEV mostly occur after 2021. Therefore, we select the data before 2020 as the sample set to fit the curve. In this case, we choose 'Export volume' as the response variable and 'year' as the predictor variable for analyzing the data. By using the least squares method(similar to problem 2), we get the curve in the situation without resistance policy as the equation below:

$$y = 0.3924e^{0.4703x} \tag{15}$$

The goodness of fit is R^2=0.9877, which proves that the accuracy of the fitted curve is high.

7.2 Analysis of Comparison

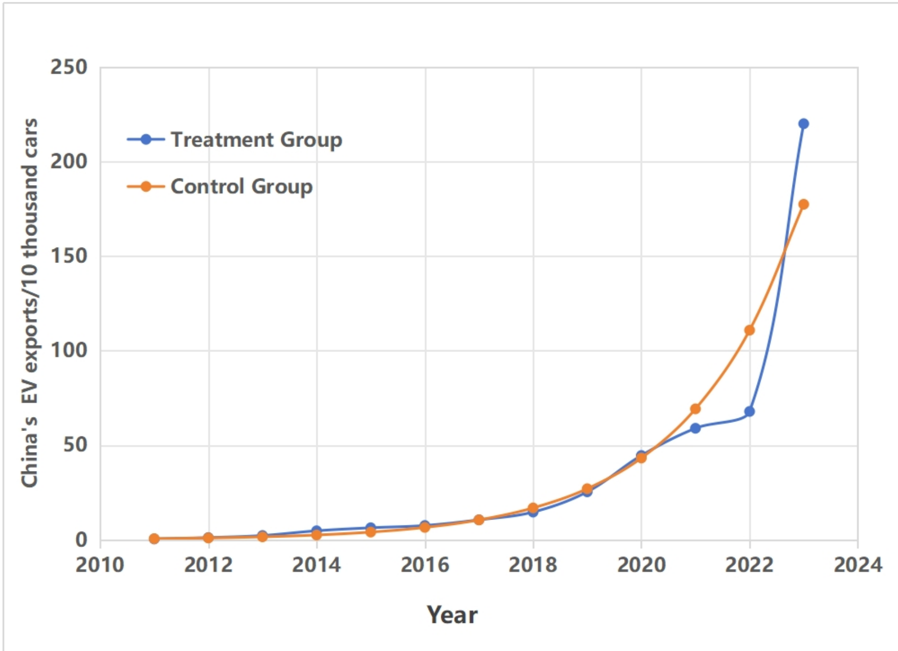


Figure 4: China's EV exports under the situations with and without resistance policy

Comparing the two sets of data in the graph, we can see that the treatment group does have lower sales in 2021 and 2022 compared to the control group, speculating that there may be fluctuations in sales during the period due to the impact of the policy. In the middle of 2023, the control-group value is higher than the treatment-group value, which means that even if there are policies in other countries that are boycotting the export of China's electric vehicles, they will not be able to curb the development of China's new energy vehicles overseas in the short term. Our team searched for the reason and found that China's electric vehicles are more competitive in terms of price, which is importantly related to the development of technological innovation in China.

8 Solution to Problem 5

8.1 Model Assumptions and Related Indicators

To analyze the impact of new energy electric vehicles (including electric buses) in cities on the ecological environment, we reviewed the information and learned that the ecological impact of traditional energy vehicles mainly comes from exhaust emissions,such as CO_2,SO_2, NO_x, O_3 and so on. In order to facilitate the analysis, only electric cars and electric buses are selected as the objects of analysis in the new energy transportation, and only CO_2 and SO_2 emissions are considered in the ecological impact of new energy vehicles.The following assumptions were made for the reasonableness of the model:

1. The data and various indicators are real and valid
2. The number of cars and buses no longer changes when analyzing the model
3. The difference in carbon and sulfur dioxide emissions between the production of new energy vehicles and traditional energy vehicles is not taken into account
4. The only two sources of electricity generation are thermal and clean energy generation, and clean energy generation does not produce any gases such as carbon dioxide and sulphur dioxide

The model we established in this problem are named as the AEVE model (Analysis of the impact of electric vehicles on the ecological environment). The symbols and constants used in this problem are as follows:

Symbol	**Definition**
SCE	total carbon emissions per day
SE	total sulfur dioxide emissions per day
α	percentage of new energy vehicles in cars
β	percentage of new energy vehicles in buses
Constant	**Definition**
Num_{car}	number of cars
Num_{bus}	number of buses
k_c	average kilometers traveled per day per car
k_b	average kilometers traveled per day per bus
CE_{tbus}	carbon emissions per kilometer traveled for each traditional energy bus
CE_{tcar}	carbon emissions per kilometer traveled for each traditional energy car
SE_{tbus}	sulfur dioxide emissions per kilometer traveled for each traditional energy bus
SE_{tcar}	sulfur dioxide emissions per kilometer traveled for each traditional energy car
E_{bus}	average electricity consumption per kilometer per electric bus
E_{car}	average electricity consumption per kilometer per electric car
y	percentage of thermal power generation in electricity generation
CE_{fire}	carbon emissions per kWh of electricity generated from thermal power generation
SE_{fire}	sulfur dioxide emissions per kWh of electricity generated from thermal power generation

Basing this model on China results in one car for every 10 people and one bus for every 250 people out of 1 million people, having a total of 100,000 cars and 4,000 buses. All the relevant data are as shown:

Constant	Value	Constant	Value
Num_{car}	100000	SE_{tbus}	10
Num_{bus}	4000	SE_{tcar}	/
k_c	76	E_{bus}	0.736
k_b	149	E_{car}	0.016
CE_{tbus}	300	CE_{fire}	997
CE_{tcar}	1100	SE_{fire}	40
y	0.8		

8.2 Analysis of Total Carbon Emissions

The formulation of SCE is

$$\begin{aligned} SCE = &(1-\alpha)Num_{car}k_c \cdot CE_{tcar} + (1-\beta)Num_{bus}k_b \cdot CE_{tbus} + \\ &\alpha Num_{car}k_c \cdot E_{car} \cdot y \cdot CE_{fire} + \beta Num_{bus}k_b \cdot E_{bus} \cdot y \cdot CE_{fire} \end{aligned}$$

- When α=0 and β=0, indicating there are no electric cars and buses in this city, the carbon emission is 2.9356×10^9 g.
- When α=1 and β=1, indicating all electric cars and buses in this city are replaced by new energy transportation, the carbon emission is 4.4686×10^8 g.

We found that when all traditional energy cars and traditional energy buses are replaced by electric transportation, the carbon emissions of a city of 1 million people are reduced by 2.48874×10^9 g, which is an 84.78% reduction in carbon emissions.

In order to visualize the impact of the change in the share of the corresponding transportation modes using electric transportation on carbon emissions, our team made a two-dimensional bar chart by varying the values of α and β to derive the results.

From the graph, it can be observed that an increase in the share of electric cars has a greater impact on carbon emissions than an increase in the share of electric buses. The reason for this is mainly because the difference in the number of cars and buses in the city is large, and even if the difference in carbon emissions between each electric bus and traditional energy bus is larger, the impact of its share is still not as large as the change in the share of new energy private cars, thus highlighting the importance of calling on citizens to purchase new energy vehicles. However, after building the equations for SE and deriving the results, a completely different result from SCE is obtained.

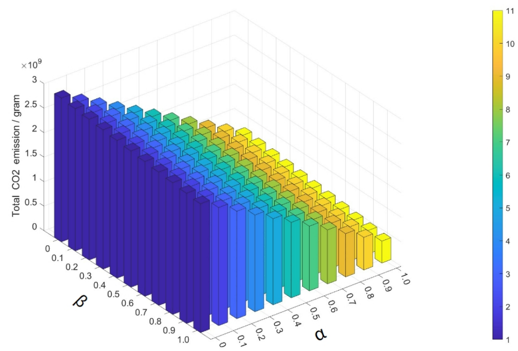


Figure 5: Total CO_2 emission

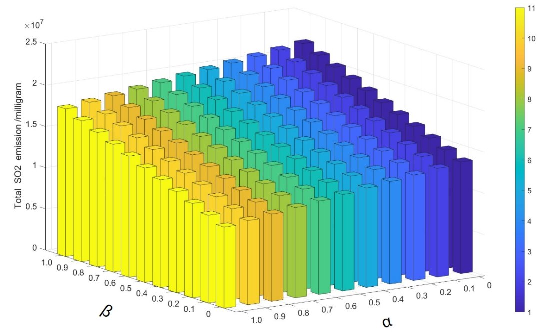


Figure 6: Total SO_2 emission

8.3 Analysis of Total Sulfur Dioxide Emissions

The formulation of SE is

$$SE = (1-\alpha)Num_{car}k_c \cdot SE_{tcar} + (1-\beta)Num_{bus}k_b \cdot SE_{tbus} + \\ \alpha Num_{car}k_c \cdot E_{car} \cdot y \cdot SE_{fire} + \beta Num_{bus}k_b \cdot E_{bus} \cdot y \cdot SE_{fire}$$

- When α=0 and β=0, indicating there are no electric cars and buses in this city, the sulfur dioxide emission is 13560000mg.
- When α=1 and β=1, indicating all electric cars and buses in this city are replaced by new energy transportation, the sulfur dioxide is 44820000mg .

In order to visualize the effect of the change in the share of corresponding transport modes that use electric transport on SO2 emissions, our team made a two-dimensional histogram by varying the values of α and β to derive the results.

It can be found that when all traditional energy cars and traditional energy buses are replaced by electric transportation, sulfur dioxide emissions in a city of 1 million people increase by 17928192mg, specifically 32.21%. This almost subverts the citizens' normal perception of new energy vehicles. Analyzing the reason, we can see that nowadays, the main source of electricity for electric vehicles nowadays comes from thermal power generation, which is based on the burning of coal, and the coal substance contains more sulfur content compared to the diesel fuel burned by ordinary cars, so in the absence of improvement in the source of power generation, the substitution of new energy vehicles may increase the sulfur dioxide emission, according to our model.

By looking at the 3D histogram, unlike SCE, an increase in the share of electric buses increases SO_2 emissions, while an increase in the share of electric cars causes a decrease in SO_2 emissions. The reason for this can be analyzed as, electric buses consume more electricity, which means burning more coal and releasing more SO_2 for the same share change.

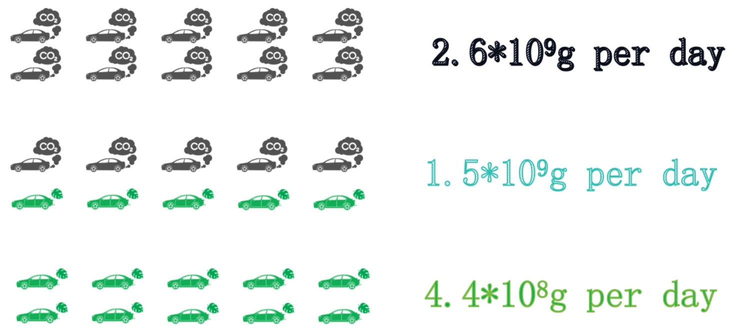


Figure 7: Carbon dioxide emissions per day

8.4 Conclusion

From a comprehensive view, with new energy transportation instead of traditional energy transportation to reduce the benefits of carbon dioxide is greater than the increase in sulfur dioxide to pay the price. Calling on urban residents to buy new energy vehicles is inevitable, the national macro-control market for electric bus company incentives is also the trend.

9 Sensitivity Analysis

In the AEVE model in problem 5, we assume the invariance of the generation sources, specifically 80% thermal power generation and 20% clean energy generation. With the development of national technology and the emphasis on environmental policy, the share of thermal power generation will decrease and the share of clean energy generation will increase. Taking a=0.5,b=0.5, we change the step size of 10% and reduce 80% to 20% gradually, to observe whether the change of carbon emissions is obvious, and if it is obvious, then it proves that the applicability of our model is strong, and it can be applied in the future when the technological development is more developed.

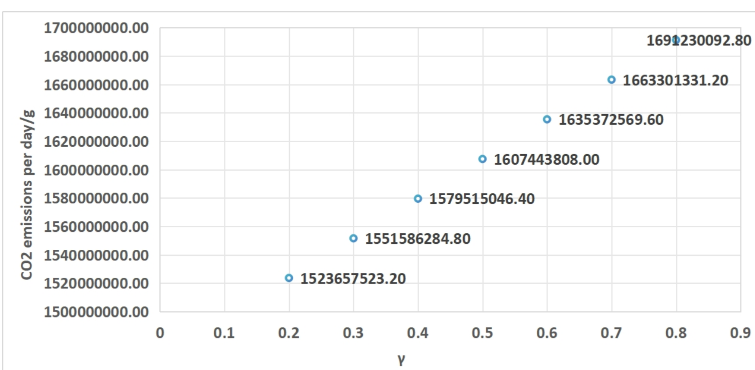


Figure 8: Sensitivity analysis

From the scatterplot above we can see that the carbon emissions are decreasing, indicating that our model has some generalizability.

However, the scatterplot also shows that the technical cost of reducing the share of thermal power generation is high, and the emission reduction effect is not as good as increasing the share of new energy vehicles, so calling on citizens to use new energy vehicles is the most effective measure to reduce emissions at present

10 Model Evaluation and Further Discussion

10.1 Strengths and Weaknesses

In all of the above processes, we analyzed the solutions and methods we applied and concluded that our essay possesses the following strengths and weaknesses.

1. **Strengths**

   Objective: Throughout the writing of this article, care has been taken to maintain the objectivity of the model. For example, in the derivation of the model in Problem 1, we used SWOT analysis and PEST analysis. Both the SWOT and PEST analysis methods contribute to objectivity by providing frameworks that facilitate structured thinking, comprehensive evaluation, and consideration of both internal and external factors.

   Innovative: In the process of modeling, we develop a predictive model in hyperbolic functional form (in Problem 2) as well as the AEVE model (in Problem 5), demonstrating our innovative approach. These innovative modeling approaches allow us to explore alternative perspectives and potentially uncover new insights.

   Reasonable: During the modeling process, we conducted a thorough analysis of the situation within the context of the real-world scenario. This enabled us to effectively interpret and explain the outcomes derived from our models by considering the dynamics and changes occurring in the actual situation, which provides a more comprehensive understanding of the subject matter.

2. **Weaknesses**

   Data Insufficiency: We made attempts using various methods and channels to search for relevant information; however, we were still unable to find sufficient data for a more comprehensive analysis. As a result, some of the parameters are based on semi-empirical guesses, and there is no specific metric that we can break down into for some of the analysis.

10.2 Further Discussion

In order to simplify the model, we have only studied the impact of new energy vehicles on the ecological environment in terms of carbon and sulfur dioxide emissions. In future research, we will take more factors into consideration, such as NO_x, CO, PM2.5, O_3 etc. so as to evaluate and quantify the ecological impact of electric vehicles in a more comprehensive and holistic way.

11 Conclusion

In conclusion, the development of new energy vehicles in China faces both opportunities and challenges. Only by continuously innovating and improving relevant policies, strengthening technology R&D and transformation, improving product quality and service levels, can China establish itself and achieve greater development in the global new energy vehicle market.

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Embrace New Energy Electric Vehicles
Make Green Travel A New Way of Life!

Dear Citizens,

We are glad to write this open letter to draw your attention to the awesome benefits of new energy electric vehicles and how they contribute to protecting the environment.

As you probably know, transportation is the main culprit of air pollution, which is one of the biggest environmental challenges we face today. **But hey, there's a solution that can help —— New Energy Electric Vehicles!**

New energy electric vehicles use unconventional vehicle fuel as their power source, producing few or zero tailpipe emissions. Based on our study, when all conventional energy cars and buses are replaced by new energy electric ones, a city of 1 million people reduces its daily carbon emissions due to transportation by 2.48874*10^9g, reducing carbon emissions by **84.78%**. This is in a situation where thermal power accounts for 80% of electricity generation. Even more exciting, when using clean energy to generate electricity, carbon emissions due to transportation will reduce by **almost 99%**, which is a great way to be carbon neutral!

The electric vehicle industry has been gaining encouraging momentum lately, with different countries worldwide making significant contributions. For example, China is making huge strides in this sector with more than 3 million electric vehicles cruising their roads; Norway also leads the world in electric vehicle adoption with over 50% of new car sales being electric;and in the United States, electric vehicles accounted for over 2% of total new car sales in 2019 and are expected to become even more popular in coming years.

Apart from reducing emissions and improving air quality, electric vehicles have several other perks too! They're cheaper to maintain compared to traditional cars since they have fewer moving parts and don't require regular oil changes. Plus, they're quieter and provide a smoother driving experience overall. All things considered, electrifying transportation is a crucial step towards shrinking our carbon footprint while enhancing our urban ecological environment.

We strongly encourage you to consider going for an electric vehicle when it's time for your next ride – join us in contributing towards a cleaner and more sustainable planet!

Sincerely,

Yours

A Appendix A

Table 5: Specific data for the top five indicators in problem 1

Year	Charging piles/million	incentive policy	battery production industry	charging station	patent
2011	1.4	40	39	30	256
2012	1.8	44	42	32	402
2013	2.1	50	46	35	519
2014	2.3	55	49	50	1117
2015	5	62	52	55	1813
2016	14	70	55	60	4229
2017	21.4	77	58	102	6915
2018	33.1	85	60	220	10451
2019	51.6	80	62	340	12401
2020	66.7	76	64	586	16236
2021	114.7	70	66	1406	17344
2022	245.1	64	68	1451	18962

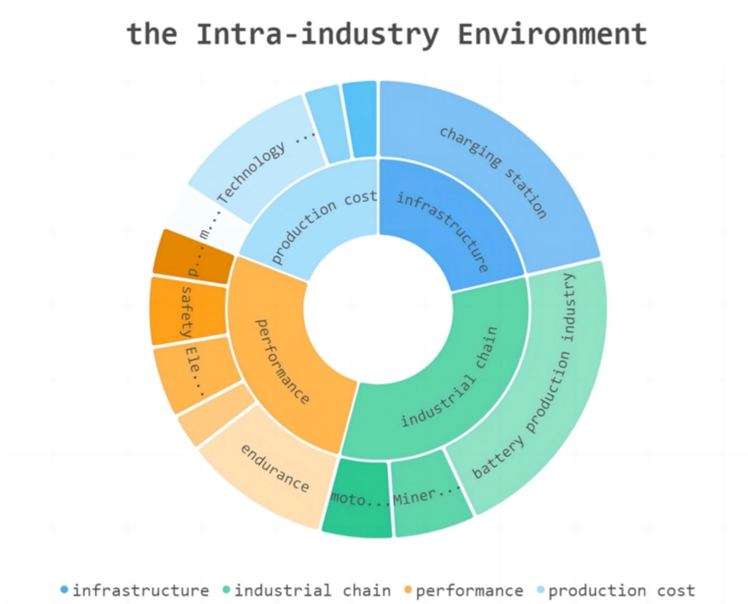

Figure 9: The data from I-F matrix of the Intra-industy Environment

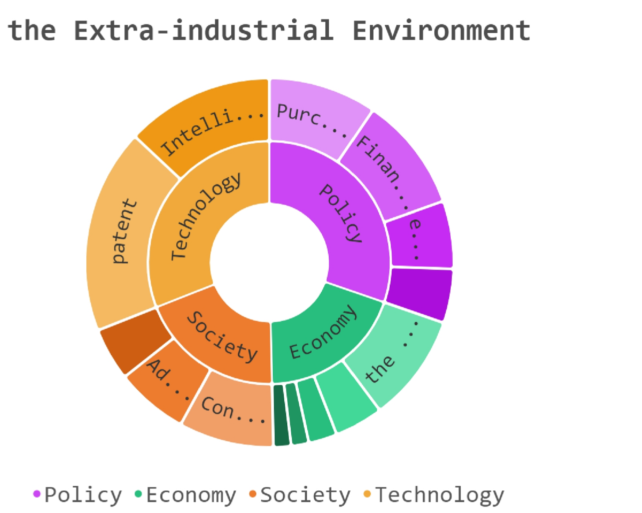

Figure 10: The data from I-F matrix of the Extra-industy Environment

Table 6: The impact value of indicators in problem 1

Factor	The Impact Value	Rank	Factor	The Impact Value	Rank
charging pile	20.16	1	safety	2.052	16
incentive policy	9.016	2	advocacy	1.98	17
battery production industry	8.712	3	energy-saving and emission-reduction assessment in various regions	1.84	18
charging station	8.64	4	financing channels and listing support	1.472	19
patent	5.568	5	urbanization development process	1.44	20
technology developing cost	4.248	6	power	1.404	21
endurance	4.212	7	Engel's coefficient	1.32	22
intelligent transportation and Internet applications	4.032	8	materials processing cost	1.296	23
financial subsidies	3.128	9	electricity consumption	1.08	24
purchase and travel promotion	2.944	10	marketing cost	1.08	25
GDP per capita	2.94	11	labor cost	1.08	26
consumer attitude	2.58	12	middle strata percentage	0.78	27
mineral extraction industry	2.376	13	electricity price	0.48	28
motor transmission system	2.112	14	fuel price	0.48	29
electricity charge	2.052	15			

B Appendix B

Listing 1: The Python Source Code of AHP

```
- import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

from openpyxl import load_workbook

workbook = load_workbook("C:\\Users\\SXD\\Desktop\\testdata.xlsx")
worksheet = workbook.active

class AHP:
"""
Incoming and preparation of relevant information
"""

def init(self, array):
Record information about the matrix
self.array = array
Record matrix size
self.n = array.shape[0]
Initializes the RI value for consistency checking
self.RI_list = [0, 0, 0.52, 0.89, 1.12, 1.26, 1.36, 1.41, 1.46, 1.49, 1.52, 1.54, 1.56, 1.58,
1.59]
Eigenvalues and eigenvectors of the matrix
self.eig_val, self.eig_vector = np.linalg.eig(self.array)
The maximum eigenvalue of the matrix
self.max_eig_val = np.max(self.eig_val)
The eigenvector corresponding to the maximum eigenvalue of the matrix
self.max_eig_vector = self.eig_vector[:, np.argmax(self.eig_val)].real
The consistency index CI of the matrix
self.CI_val = (self.max_eig_val - self.n) / (self.n - 1)
The consistency ratio of the matrix CR
self.CR_val = self.CI_val / (self.RI_list[self.n - 1])

"""
Consistency judgment
"""

def test_consist(self):
Consistency index CI and consistency ratio CR of the printed matrix
print("The␣CI␣value␣of␣the␣judgment␣matrix␣is␣" str(self.CI_val))
print("he␣CR␣value␣of␣the␣judgment␣matrix␣is" str(self.CR_val))
Make a consistency test judgment
if self.n == 2:  When there are only two subfactors
```

```
print("There are only two subfactors and no consistency issues")
else:
if self.CR_val < 0.1:  If the CR value is less than 0.1, it can pass the consistency test
print("The CR value of the judgment matrix is" str(self.CR_val) + ",Pass conformance test")
return True
else:  If the CR value is greater than 0.1, the consistency test fails
print("The CR value of the judgment matrix is" str(self.CR_val) + "Failed the conformance test")
return False

"""
The eigenvalue method is used to calculate the weights
"""

def cal_weight__by_eigenvalue_method(self):
# The weight is obtained by normalizing the eigenvector corresponding to
# the maximum eigenvalue of the matrix
array_weight = self.max_eig_vector / np.sum(self.max_eig_vector)
# Print weight vector
print("The weight vector calculated by eigenvalue method is\n", array_weight)
# Returns the value of the weight vector
return array_weight


if name == "__main__":
# Give judgment matrix
b = []
for i in range(1, 5):
data = []
for j in range(1, 5):
data.append(worksheet.cell(row=i, column=j).value)
b.append(data)
print(b)
b=np.array(b)


AHP(b).test_consist()
weight3 = AHP(b).cal_weight__by_eigenvalue_method()
```

Listing 2: The Python Source Code of Critical method

```
import pandas as pd
import numpy as np

from openpyxl import load_workbook

```

```
workbook = load_workbook("C:\\Users\\SXD\\Desktop\\testdata.xlsx")
worksheet = workbook.active

#Defining transition function
def costToMax(A):#Cost
x = np.max(A)
for i in range(0,A.shape[0]):
A[i] = x-A[i]
return A

def middleToMax(A,a):#Middle
x = np.max(np.abs(A-a))
for i in range(0,A.shape[0]):
A[i] = 1-np.abs(A[i]-a)/x
return A

def rangeToMax(A,a,b):#Range
u = a-np.min(A)
v = np.max(A)-b
M = v
if u>=v:
M=u
for i in range(0,A.shape[0]):
if A[i]<=a:
A[i] = 1-(a-A[i])/M
elif A[i]>=b:
A[i] = 1-(A[i]-b)/M
else:
A[i] = 1
return A

#Define normalized function:
def standardize(A):
for j in range(0,A.shape[1]):
sum = 0
for i in range(0,A.shape[0]):
sum = sum+A[i][j]**2
for i in range(0,A.shape[0]):
A[i][j] = A[i][j]/np.sqrt(sum)
return A


def main():
Data = []
for i in range(1, 6):
data = []
for j in range(1, 6):
```

```
        data.append(worksheet.cell(row=i, column=j).value)
        Data.append(data)
        print(Data)
        Data = np.array(Data)

        Data = np.transpose(Data)
        Data = standardize(Data)

        #relative property
        the=np.std(Data,axis=0)
        print(the)

        #contradictoriness
        Data=np.transpose(Data)
        r=np.corrcoef(Data)
        f=np.sum(1-r,axis=1)
        print(f)
        #Calculated information load
        c=the*f

        #calculate weights
        w=c/sum(c)
        print(w)
        main()
```

Listing 3: The Matlab Source Code of GRA Predict

```
        %Create sign variables a(development coefficient) and b(grey action)
        syms a b;
        c = [a b]';

        %Primitive series sale
        sale =
            [0.8159,1.3,1.8,7.5,32.9,50.2,76.8,124.7,120.6,136.7,350.7,688.7];
        n = length(sale);

        %Add the original series sale to get series saleadd
        saleadd = cumsum(sale);

        %Do adjacent mean generation for series saleadd
        for i = 2:n
        C(i) = (saleadd(i) + saleadd(i - 1))/2;
        end
        C(1) = [];

        %Construct data matrix
        saleadd = [-C;ones(1,n-1)];
        Y = sale; Y(1) = []; Y = Y';
```

```
        %Calculate parameters a(development coefficient)
        %and b(grey action) using least squares method
        c = inv(saleadd*saleadd')*saleadd*Y;
        c = c';
        a = c(1); b = c(2);

        %Forecast subsequent data
        ForecastSale = []; ForecastSale(1) = sale(1);
        for i = 2:(n+10)
        ForecastSale(i) = (sale(1)-b/a)/exp(a*(i-1))+ b/a;
        end

        %The series ForecastSale is reduced and reduced to obtain the
            predicted data
        predictSale = []; predictSale(1) = sale(1);
        for i = 2:(n+10)
        predictSale(i) = ForecastSale(i) - ForecastSale(i-1); %Get the
            predicted data
        end

        disp('predicted␣datas␣are␣');
        predictSale
```

Listing 4: The Matlab Source Code of Spearman correlation analysis

```
        z=log(sale)
        [r,p]=corr(Score,sale)
```

Listing 5: The Matlab Source Code of AEVE Model

```
Numcar=100000,Numbus=4000;
%a is Electric cars account for the share of cars
%b is Electric buses account for the share of buses
a=0,b=0;
kc=76,kb=149;
CEtbus=1100,CEtcar=300;
Ebus=0.736,Ecar=0.016;
%y is thermal power generation that accounts for the total amount of
    electricity generated
y=0.8;
CEfire=997
SCE=(1-a)*Numcar*kc*CEtcar+(1-b)***Numbus***kb*CEtbus+a*Numcar*kc*Ecar*y*
    CEfire+b*Numbus*kb*Ebus*y*CEfire
SEfire=40;
SEtcar=1;
SEtbus=10;
SE=(1-a)*Numcar*kc*SEtcar+(1-b)***Numbus***kb*SEtbus+a*Numcar*kc*Ecar*y*SEfire
    +b*Numbus*kb*Ebus*y*SEfire
```

Listing 6: The Matlab Source Code of Plot,language=matlab

```
% %%pro3 plot
clc;clear;figure;
prob3 = xlsread("prob3.xlsx");
x = prob3(:,1);
y_global = prob3(:,2);
y_tradition = prob3(:,4);
yyaxis left
p1 = plot(x,y_tradition,'-s','MarkerSize',6.5,LineWidth=2);
ylim([5000 10000]);
y_ev = prob3(:,3);
ylabel('Sales(10 thousand cars)','FontSize',15);
yyaxis right
p2 = plot(x,y_ev,'-d','MarkerSize',6.5,LineWidth=2);
legend('Traditional energy vehicle sales','New energy electric vehicle sales
    ','FontSize',12)
title("Sales for new energy electric vehicles and traditional vehicles",'
    FontSize',15);
xlabel('Year','FontSize',15);
ylabel('Sales(10 thousand cars)','FontSize',15);
%%pro5 plot
clc;clear;
figure;
%a is Electric cars account for the share of cars
%b is Electric buses account for the share of buses
a = 0:0.1:1;
b = a;
[A,B] = meshgrid(a);
Numcar=100000;
Numbus=4000;
kc=76;kb=149;CEtbus=1100;CEtcar=300;Ebus=0.736;Ecar=0.016;
% y is thermal power generation that accounts for
% the total amount of electricity generated
y=0.8;
CEfire=997;
SCE = (1-A)*Numcar*kcCEtcar+...
*       (1-B)***Numbus***kb*CEtbus+...
A*Numcar*kc*Ecar*yCEfire+...
*       B*Numbus*kb*Ebus*y*CEfire;
surfl(a,b,SCE);
width = 0.5;
figure
bar3(SCE,width);
colorbar;
set(gca,'xticklabel
```

```
',{'0','0.1','0.2','0.3','0.4','0.5','0.6','0.7','0.8','0.9','1.0'},'FontSize', 14);
set(gca,'yticklabel',{'0','0.1','0.2','0.3','0.4','0.5','0.6','0.7','0.8','0.9','1.0'});
hXLabel = xlabel(' Electric cars account for the share of cars','FontSize', 15);
hYLabel = ylabel('Electric buses account for the share of buses','FontSize', 15);
set(gca,'XGrid', 'off', 'YGrid', 'off','ZGrid', 'on')
zlabel(' Total  CO2  emission / gram');
hTitle = title('Total CO2 emission/gram');
SEfire=40;
SEtcar=1;
SEtbus=10;
SE=(1-A)*Numcar*kcSEtcar+...
*(1-B)***Numbus***kb*SEtbus+...
A*Numcar*kc*Ecar*ySEfire+...
*B*Numbus*kb*Ebus*y*SEfire;
width = 0.5;
figure
bar3(SE,width);
colorbar;
set(gca,'xticklabel',{'0','0.1','0.2','0.3','0.4','0.5','0.6','0.7','0.8','0.9','1.0'},'FontSize', 14);
set(gca,'yticklabel',{'0','0.1','0.2','0.3','0.4','0.5','0.6','0.7','0.8','0.9','1.0'});
hXLabel = xlabel(' Electric cars account for the share of cars','FontSize', 15);
hYLabel = ylabel('Electric buses account for the share of buses','FontSize', 15);
set(gca,'XGrid', 'off', 'YGrid', 'off','ZGrid', 'on')
zlabel(' Total  SO2  emission /milligram');
hTitle = title('Total SO2 emission/gram');
set(hTitle, 'FontSize', 17, 'FontWeight' , 'bold');
```