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Multi-dimensional analysis of the impact of new energy vehicles on the urban ecological environment and prediction of future

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Abstract. This study examines the development indicators of China's new energy vehicle industry using clustering and multiple regression methods. The indicators are divided into internal and external aspects: external factors, such as the degree of completeness of charging facilities, market demand, policies and regulations, and internal factors, mainly brand types and power costs. By comparing the forecasting models of its industry data, including the exponential smoothing model, grey forecasting model and Brownian forecasting model. The forecast results show that this industry in China maintains a positive development trend in the next ten years. It shows that the development prospect of electric vehicles is very bright.The population competition model is used to model the competitive situation between new energy and traditional energy vehicles, and it is concluded that new energy vehicles are replacing traditional fuel vehicles and promoting the transformation of the automotive industry to be environmentally friendly and efficient.Collect the key measures and points in time that countries have taken to target the development of this industry in China. Analysing the data on the development of the industry before and after these events, it is found that external factors, such as other countries' policies, may inhibit the industry's growth. If other countries take action to thwart this industry in China, it may temporarily break its growth or even lead to a short-term industry recession.

Keywords: New Energy Vehicle Industry, Forecasting Models, Population Competition Models, Carbon Emissions and Ecological Footprint, Environmental Protection and Emission Reduction.

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1. Introduction

Nowadays, the development of clean and sustainable energy has become a global consensus. Exploring its development trend through mathematical modelling and data research is of great significance to China's industrial development and global energy sustainability. The adoption of electric vehicles significantly reduces urban air pollution, presenting a viable solution to mitigate climate change impacts.[1]

2. Quantitative Analysis and Projection of New Energy Vehicle Industry Development in China

Utilizing clustering, multiple regression, and advanced forecasting models, this study analyzes the trajectory and impact of China's new energy vehicle (NEV) industry. Data from authoritative sources is mathematically examined to envisage NEVs' ascendancy in an evolving automotive sector, highlighting a shift towards sustainable urban transport driven by policy, market demand, technological innovation, and ecological considerations.

2.1. Multiple regression and cluster analysis of development indicators

2.1.1. Data collection and collation

A variety of data sources were used, including the China Statistical Yearbook, the China Energy Statistical Yearbook and the National Bureau of Statistics. For missing data, intermediate processing or interpolation was used to supplement data for subsequent years.

2.1.2. Conducting regional clustering to analyse relevant differences

Different provincial administrative regions are selected as samples, and there are 44 regions corresponding to the ownership of public class charging piles from December 2018 to July 2022 in the sample indicators, and the systematic clustering mines useful information to observe the provincial administrative regions.

The steps of systematic clustering analysis are as follows:

a. Defining sample distances

To start the classification, n samples are taken as n classes and the distance between them is calculated. The distance d_{ij} between the two samples i,j was calculated using the Euclidean distance calculation method:

$$d_{ij} = \sqrt{(x_1-y_1)^2 + (\mathrm{x}_2-\mathrm{y}_2)^2 + \cdots + (\mathrm{x}_\mathrm{n}-\mathrm{y}_\mathrm{n})^2} \tag{1}$$

b. Calculation of inter-class distances

Define the distance between classes, by whose calculation the classification can be achieved

c. Number of clusters selected

Observe the affinity of the relationship between the variables with the genealogy chart, using SPSS for systematic cluster analysis plotting provides a number of scenarios, see Figure 1.In order to make the number of clusters more objective, the elbow rule was applied to correct and determine the number of classifications, to find the optimal K-value, to determine the optimal number of clustering groups based on coefficients in the centralised schedule in the results of the cluster analysis, and to draw the elbow diagram, as shown in **Figure 1**.

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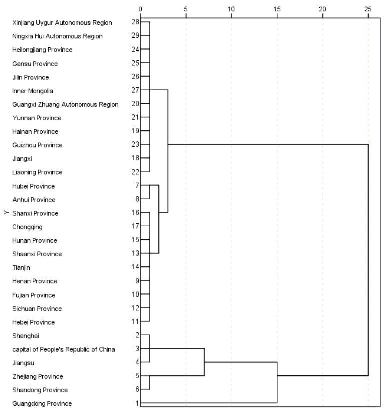

Figure 1. genealogical chart

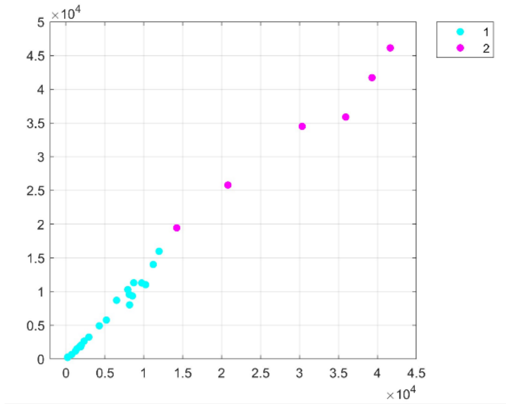

Figure 2. Scatterplot of clustering results

The contour coefficient takes the value between [-1,1], and the closer it is to 1, the better the clustering effect is. It is observed that when clustering into two classes, the contour coefficient is close to 0.8, and its clustering effect is perfect. Therefore, the number of clusters selected after the results of the systematic clustering analysis is once again confirmed to be 2, which is finally combined with the number of set clusters to be 2.

d. Clustering

Combining the above clustering results with **Figure 2** identifies the samples clustered into two categories. The first category contains the five provincial administrative regions of Shanghai, Jiangsu Province, Zhejiang Province, Shandong Province, and Guangdong Province, and the second category contains the remaining 24 regions.

e. Analysis of results

Clustering results indicate that the development trends of new energy vehicle charging piles vary across provinces. Two main categories emerge: suitable development areas (SH, JS, ZJ, SD, GD) in the east coast and Yangtze River belt, with strong economies, high car ownership, and ample government support; and other regions with varying city grades, policies, and economic strengths, like Beijing and Hubei, which prioritize congestion management, or Ningxia and Xinjiang, with lower economic levels and car ownership.Expanding electric vehicle charging infrastructure is essential for widespread adoption, though it necessitates advancements in grid management to ensure stability.[2]

2.1.3. Main factors and their impact on the industry

The transition to electric vehicles is impeded by the entrenched dominance of fossil fuel infrastructure, suggesting a need for strategic policy interventions.[3] Using multiple linear regression and systematic clustering, we identified regional disparities in new energy electric vehicle (NEV) development. Key factors driving NEV sales include charging infrastructure, market demand, and other variables. An empirical analysis of China's NEV industry, considering both external (charging facilities, demand, policies) and internal factors (brand diversity, power cost), was conducted to draw insights.

(1) Charging infrastructure

The construction and coverage of regional charging infrastructure directly impact the reliability and convenience of electric vehicle charging, which can significantly advance the market development of new energy electric vehicles. Combining the data of six annual average charging piles (10,000 piles) in China in previous years, a three-dimensional pie chart was created to visualise the increasing share of charging piles year by year, as shown in **Figure 3**.

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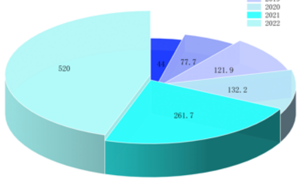

Figure 3. Annual number of vehicle piles

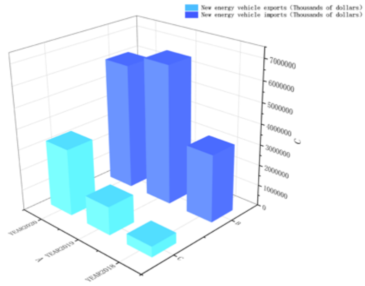

Figure 4. Total exports and imports of automobiles

(2) Market demand factors

New energy in line with the current sustainable development road demand, energy saving and emission reduction is the trend; with the increase in the number of manufacturers, market demand is increasing, and there is a great deal of traction on the development of the industry. China's past years, the new energy vehicle import and export amount (thousands of yuan) selected displayed in the following **Figure 4** observation of new energy electric vehicle import and export amount roughly showing a year-on-year increase in the trend of visible trade flows, domestic and foreign market demand increased! Consumer acceptance of electric vehicles hinges on improving range anxiety, charging convenience, and initial costs.[4] Sales in unrestricted areas generally trend upward and are higher than in restricted areas, indicating that regional restriction policies significantly impact the development of new energy vehicles. Government incentives play a crucial role in accelerating electric vehicle adoption, but long-term strategies require market-driven forces to sustain growth.[5]

2.2. Projections of development trends over the next decade

2.2.1. Grey Forecast and Future Prospects Analysis

Grey system theory provides an effective forecasting tool in scenarios with limited or incomplete information, showing promising application in predicting electric vehicle adoption trends.[8] Grey prediction models are suitable for predicting small samples and incomplete information.

(1) Modelling

Establishing the grey differential equation

$$x^{(0)}(k) + az^{(1)}(k) = b, k = 2,3,\cdots,n \tag{2}$$

The corresponding predicted values can be obtained

$$\delta(k) = \frac{\left|x^{0}(k) - \hat{x}^{(0)}(k)\right|}{x^{(0)}(k)}, k = 1,2,\cdots,n, \tag{3}$$

When $x^{(0)}(1) = x^{(0)}(1)$, if $\delta(k) < 0.2$, it can be considered that the general requirements are met; if $\delta(k) < 0.1$, it is considered that the higher requirements are met.

(2) Analysis of projected results

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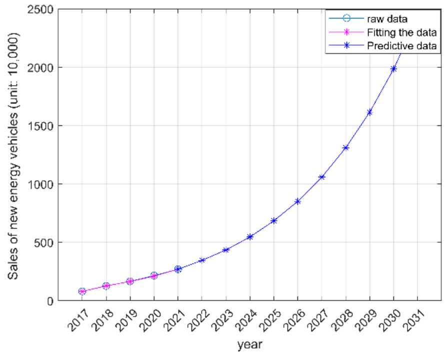

Figure 5. Chart of predicted results

Looking at **Figures 5**, from the perspectives of technology, market, policy and infrastructure, the growth of patents for new energy vehicles, the increase in global market share, government support and the growth in the number of charging piles all bode brightly and favourably for the development of electric vehicles in the next decade. Reducing battery costs is key to enhancing the competitiveness of new energy vehicles, requiring targeted research and development investments.[9]

2.3. Modelling the evolution of the long-term vehicle energy mix

The population competition model was adopted because, after analysing the impact of new energy electric vehicles on the global traditional energy automotive industry, it was decided to adopt this model given the relationship between these two opposing automotive industries in the global environment, i.e. the competition between two different types of "populations" in the context of sharing global resources. Hydrogen could play a vital role in decarbonizing various sectors, including transportation, when produced from renewable energy sources.[10]

In environments with limited natural resources, stagnant growth models are often used and incorporate the competing roles of electric and conventional energy vehicles. The ordinary differential equation model for electric vehicles is as follows.

$$\frac{dx_1(t)}{dt} = r_1 x_1 \left(1 - \frac{x_1}{N_1} - \sigma_1 \frac{x_2}{N_2}\right) \tag{5}$$

The ordinary differential equation model for a conventional energy vehicle is as follows

$$\frac{dx_2(t)}{dt} = r_2 x_2 \left(1 - \frac{x_2}{N_2} - \sigma_2 \frac{x_1}{N_1}\right) \tag{6}$$

where N_1, N_2 denotes the environmental capacity of electric vehicles and the environmental capacity of conventional energy vehicles, respectively, and x_1, x_2 denotes the number of electric vehicles globally and the number of conventional energy vehicles nationally in the last 10 years, respectively, as shown in Table 1.

Table 1. Use of data sheets

vintages	Global conventional vehicle sales (units)	Global electric vehicle sales (millions of units)
2013	57617100	0.11
2014	60905600	0.29
2015	62705700	0.55
2016	66817600	0.77
2017	68325000	1.22
2018	68157900	1.98

Table 1. (continued).

2019	65504300	2.26
2020	56000700	3.24
2021	58180800	6.77
2022	58150200	10.52

Over the past decade, Table 1 indicate a consistent trend: global sales of conventional vehicles have been gradually declining, forecast to become extinct, while sales of new energy electric vehicles have been rising, approaching their numerical limits. High greenhouse gas emissions and environmental pollution are driving the automotive industry towards cleaner, greener energy forms. In summary, new energy electric vehicles are replacing traditional fuel-powered vehicles, impacting the global traditional energy automobile industry. Long-term, new energy vehicles are expected to dominate the market, leading to a more environmentally friendly, efficient, and sustainable transportation model.

3. Conclusion

his comprehensive study employed mathematical models and data analysis to assess the impacts of new energy vehicles on urban ecological environments and predict trends in China's industry. Clustering and regression methods provided insights into development indicators. External factors like charging infrastructure, market demand, and policies, coupled with internal factors like brand diversity and power costs, shape the industry. Clustering revealed regional disparities in charging facilities and adoption rates, influenced by economic strength and government support. Forecasting models project a positive outlook for the new energy vehicle industry, highlighting the shift from traditional fuel vehicles. While electric cars have lower operational carbon footprints, efforts are needed to reduce emissions from battery production and electricity generation. These findings underscore the need for continued innovation and strategic policymaking towards sustainable energy utilization and carbon footprint reduction. Future research should focus on refining prediction models and exploring global implications of China's advancements.

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