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A Study on the Future Development Prospects of New Energy Electric Vehicles Based on the Trend Determination Method

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Abstract: The rapid development of new energy electric vehicles (NEEVs) has garnered significant attention globally. This paper aims to analyze and understand the factors influencing the development of NEEVs and their potential impact on both the domestic and global automotive industries. Initially, this paper identifies key factors that significantly impact the industry's development and establish a multiple linear regression model to analyze these factors. Subsequently, this paper applies exponential smoothing and grey correlation analysis to conduct a comprehensive forecast of trends from multiple perspectives. Our analysis predicts that NEEVs will experience a steady rise over the next decade, especially in market share, making them increasingly competitive against traditional vehicles. Furthermore, NEEVs are poised to significantly disrupt the traditional energy vehicle industry through technological innovation and market demand.

1. Introduction

The rapid ascent of new energy electric vehicles (NEEVs) in the global automotive market, especially notable in China, has attracted considerable scholarly and industrial attention. In Yu et al.'s paper, they point out that China's aggressive implementation of incentive policies has not only spurred the growth of its NEEV sector but has also established the nation as a pivotal player in this innovative industry domain[1].

The burgeoning popularity of NEEVs globally necessitates a thorough examination of the multifaceted drivers influencing their development and the consequent ramifications for both the domestic and international automotive markets[2]. Prior research has highlighted a range of socio-economic and technological factors that contribute to this shift, including governmental incentives, advancements in battery technology, and changing consumer preferences[3][4].

This paper employs a variety of analytical models to address and forecast the ongoing and future impacts of NEEVs. Utilizing methods such as exponential smoothing, multiple linear regression, and grey correlation analysis, this study systematically evaluates how these vehicles are poised to reshape the automotive landscape. Initial investigations indicate that market share growth is a significant indicator of NEEV development success, suggesting a competitive edge over traditional combustion engine vehicles in the coming decade[5].

Our study aims to extend the existing body of knowledge by providing a nuanced analysis of the critical factors steering the industry's trajectory. By integrating diverse methodological approaches, this paper offers a comprehensive perspective on the potential for NEEVs to disrupt traditional automotive markets, driven by technological innovation and shifting market demands.

2. Data Preprocessing

The primary sources of data for this study include the National Bureau of Statistics of China, augmented by supplementary data from reliable new energy vehicle websites and industry publications such as China Fund News. This diverse sourcing ensures a comprehensive dataset reflective of the industry-wide landscape.

2.1 Handling of Missing Data Values

Data completeness varies across datasets, influenced by the disparate data collection practices of various departments and the time periods covered. To enhance the integrity and analytical robustness of our data, missing values are addressed using a regression interpolation method based on sequential trends. This approach mitigates the potential bias caused by non-random data absence, thereby improving the overall data quality.

2.2 Data Standardization

Due to the different units and orders of magnitude of each variable, the data of each variable can be standardized in order to facilitate the construction of multiple regression models. In this paper, the Z-score standardization method is used to process the data. It can be expressed as follows:

$$z = \frac{x-\mu}{\sigma} \tag{1}$$

Where x represents the data point, μ is the mean of the dataset, and σ is the standard deviation. Standardizing data in this manner ensures that the variables contribute equally to the analysis, facilitating more reliable multivariate regression model construction.

3. Multiple Linear Regression Model

3.1 Description of Multiple Linear Regression Model

A multiple linear regression model is used to explain the linear relationship between the explained variable and the explanatory variables of other multiple variables. The mathematical model[6] is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_p x_p + \varepsilon \tag{2}$$

The above equation represents a p-element, meta-linear regression model, in which it can be seen that there are p explanatory variables. It represents that the change in the explanatory variable y can be composed of two parts: the first part is the linear part of the change in y caused by the change of p explanatory variables x. The second part, the part of the y change caused by random variables ε can be replaced, which can be called random error, and the parameters in the formula β_0, β_1, β_2, …, β_P are all unknown quantities of the equation, which can be expressed as partial regression constants and regression constants.

3.2 Model Establishment

3.2.1 Indicator Selection for Model Construction

To construct a mathematical model that predicts the development of new energy vehicles, this paper employed the least squares method to analyze data from a new energy vehicle database. The variables were selected based on their correlation with the sales of new energy vehicles, denoted by y. The chosen indicators are as follows: year-on-year growth in energy production (x_1), the amount of government subsidies (x_2), the number of invention patents for new energy vehicles (x_3), and the market share of electric vehicles (x_4) [7]. The model is formulated by the following expression:

$$y = \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon \tag{3}$$

This equation integrates these indicators to estimate the impact of each on the sales performance of new energy vehicles, providing a comprehensive view of the factors driving market dynamics.

3.2.2 Regression Fitting Analysis

Multiple linear regression analysis was conducted using SPSS software to assess the impact of various factors on new energy vehicle sales[8]. The regression results, summarized in Table 1, provide significant insights into the relationships between the predictors and the dependent variable.

Table 1: Linear regression analysis

	Non-normalized coefficient		Normalization factor			
	B	Standard error	Beta	t	P_value	BRIGHT
Constant	-215.994	64.713	——	-3.338	0.012**	——
Energy	11.815	5.032	0.04	2.348	0.051*	1.711
Subsidize	14.841	4.69	0.07	3.164	0.016**	2.922
Patents	0.006	0.02	0.01	0.289	0.781	7.23
Market	242.658	7.695	0.976	31.535	0.000***	5.696
R^2	Adjust R^2	F	P			
0.999	0.998	1486.001	0.000***			

The analysis indicated highly significant results, as evidenced by an F-test with a P-value of less than 0.0001 ($P < 0.000$***), suggesting strong statistical evidence against the null hypothesis that the regression coefficients are zero. Consequently, these predictors are deemed to significantly influence the dependent variable, confirming its suitability and robustness.

To assess the potential issue of multicollinearity among predictors, Variance Inflation Factor (VIF) scores for each variable were calculated to be below 10, which suggests that multicollinearity does not unduly influence the model's estimates, supporting the independence of the explanatory variables and the stability of the regression coefficients.

The regression equation, derived from our analysis, is presented as follows:

$$y = -215.994 + 11.815x_1 + 14.841x_2 + 0.006x_3 + 242.658x_4 \tag{4}$$

This model provides a quantitative framework for predicting the dependent variable based on changes in the predictors x_1, x_2, x_3, and x_4.

3.2.3 Model Verification

The adequacy of the regression model is evaluated by comparing the true values against the predicted values. The corresponding fitting effects are visually represented in Fig 1.

Figure 1: Fitting renderings

Fig 1 demonstrates a close alignment between the actual and predicted values. This strong correspondence shows that the model accurately captures underlying trends in the data and validates the usefulness of the regression formula, highlighting its potential as a valuable tool for exploring the impact of various factors on the growth of the NEV industry.

3.3 Analysis of the Results

The relative impacts of various indicators on the sales of new energy vehicles are visually represented in Table 2. This graphical representation clearly delineates that market share has the most significant influence on the development of new energy vehicles, followed by the amount of policy subsidies, energy production, and the number of R&D patents.

Table 2: The impact of each indicator on the sales of new energy vehicles

	Growth of energy production	Amount of subsidies	Number of patents	Market share
New Energy Vehicle Sales	0.04	0.07	0.01	0.9766

Firstly, market share is pivotal because it enhances the industry's scale advantages, enriches the industrial chain, and attracts superior technical talent, which collectively expedite the advancement of new energy vehicles. Government policy subsidies rank second in terms of impact. These subsidies are crucial as they allow governmental bodies to influence the new energy vehicle market directly, facilitating the industry's growth and the adoption of new technologies.

Conversely, the impact of the number of R&D patents and energy production on new energy vehicle sales is more modest. R&D activities cannot be directly translated into immediate market demand or expansion of industry scale. This indicates that other market dynamics and external factors have a greater impact on NEV sales. Energy production primarily affects the operational aspects and utility of these vehicles rather than their production and development. Since new energy vehicles aim to decrease energy consumption and mitigate environmental pollution, energy production will be directly affected.

4. Exponential Smoothing

4.1 Description of Exponential Smoothing

Exponential smoothing is an effective method for making predictions based on historical data series, with the selection of the smoothing coefficient crucial for the model's accuracy[9].

Let the historical data time series of indicator values be $x1$, $x2...xt...$, and the smoothing coefficient α, then the smoothing formula is: $\alpha \in (0,1)$

$$S_t^{(1)} = \alpha \times x_t + (1-\alpha) \times S_{t-1}^{(1)} \tag{5}$$

$$S_t^{(2)} = \alpha \times S^{(1)}{}_t + (1-\alpha) \times S_{t-1}^{(2)} \tag{6}$$

$$S_t^{(3)} = \alpha \times S^{(2)}{}_t + (1-\alpha) \times S_{t-1}^{(3)} \tag{7}$$

Where is the $x1$ measured function of the t time series; $S_t^{(1)}$is the first exponential smoothing value of the t time series; $S_t^{(2)}$is the second exponential smoothing value of the t time series; $S_t^{(3)}$ is the third exponential smoothing value of the t time series.

The primary, quadratic and cubic exponential smoothing time predictions are as follows:

(1) Primary exponential smoothing method prediction model

$$\hat{x}_{t+T} = S_t^{(1)} = \alpha \times x_t + (1-\alpha) \times \hat{x}_{t+T-1} \tag{8}$$

Where $\hat{x}_{t+T}$ is the predicted value of the t+T time series and the predicted value of the $\hat{x}_{t+T-1}$ is t+T-1 time series.

(2) Quadratic exponential smoothing method prediction model

On the basis of the primary exponential smoothing method, the quadratic exponential smoothing method can be obtained after another smoothing, and the model is shown in the following Fig:

$$\hat{x}_{t+T} = \alpha_t + b_t T \tag{9}$$

$$a_t = 2S_t^{(1)} - S_t^{(2)} \tag{10}$$

$$b^t = \frac{\alpha}{1-\alpha}\left(S_t^{(1)} - S_t^{(2)}\right) \tag{11}$$

Where a_t and b_t is the parameters of the model predicted by the quadratic exponential smoothing method.

(3) Cubic exponential smoothing prediction model

On the basis of the quadratic exponential smoothing method, the cubic exponential smoothing method can be obtained after smoothing again, and the model is shown in the following Fig:

$$\hat{x}_{t+r} = a_t + b_t T + c_t T \tag{12}$$

$$a_t = 3S_t^{(1)} - 3S_t^{(2)} + S_t^{(3)} \tag{13}$$

$$b_t = \frac{\alpha}{2(1-\alpha)^2}\left[(6-5\alpha)S_t^{(1)} - 2(5-4\alpha)S_t^{(2)} + (4-3\alpha)S_t^{(3)}\right] \tag{14}$$

$$c_t = \frac{\alpha^2}{2-(1-\alpha)^2}\left[S_t^{(1)} - 2S_t^{(2)} + S_t^{(3)}\right] \tag{15}$$

Where a_t, b_t, c_t is the cubic exponential smoothing method to predict the model parameter values.

4.2 Model Establishment

4.2.1 Trend Analysis

The initial step is to analyze the trends in the historical data series in order to determine which exponential model to use. Analyze the factors affecting the development of new energy vehicles from four key indicators: charging pile ownership, car sales, market share and car ownership. For each of these indicators, this paper draws and examines their historical data trends to understand their progression and identify patterns that will inform our forecasting approach. The results are shown in Fig 2.

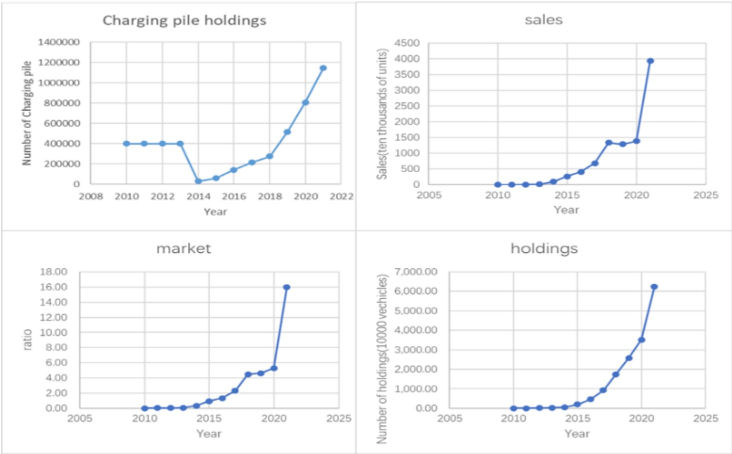

Figure 2: Trend chart

Fig 2 illustrates the fluctuating trends in the number of charging piles, with a noticeable decline from 2010 to 2014 followed by an upward trend from 2014 to 2021. For the sales, the market share and the holdings of new energy vehicle, the trends appear to be linear, making the all satisfy the second order exponential smoothing.

4.2.2 Model Verification

This paper utilized SPSS software to apply exponential smoothing for forecasting the next ten years of data across four indicators. The results are shown in Table 3. Subsequently, this paper analyzed the model's fit to evaluate its accuracy and reliability.

Table 3: Fitting effect

Fit statistics	average value	standard error	minimum	maximum
R square	0.705	0.169	0.558	0.927
Normalize BIC	13.208	8.884	2.426	24.177

From Table 3, it can be observed that the average R^2 value approaches 1, indicating a strong fit across the four indicators. Additionally, the relatively low standard error of 0.169 suggests that the variability in the R^2 values among the indicators is minimal, supporting the consistency of the model's performance. The normalized Bayesian Information Criterion (BIC), being lower, further attests to the model's accuracy. A smaller BIC value, calculated using the formula:

$$\mathrm{BIC} = \mathrm{n}\ln\left(\frac{\mathrm{RSS}}{\mathrm{n}}\right) + \mathrm{k}\ln(\mathrm{n}) \tag{16}$$

Where n is the number of samples, RSS is the residual sum of squares, and k is the number of parameters, indicates a good balance between model fit and complexity. This combination of high R^2 values, low standard error, and small BIC suggests that the model is well-constructed and reliable for predictive purposes.

4.3 Analysis of the Results

Using the above model to predict the data of each indicator in the next ten years, the values are shown in Table 4.

Table 4: Predictions for the next 10 years

Time	Charging Pile Holdings	Sales	Market	Holdings
2022	1449075.3	4035.222	17.5948	9,253.43
2023	1756179.581	4759.06	21.26234	12533.3
2024	2063283.862	5482.897	24.92988	16086.09
2025	2370388.143	6206.735	28.59742	19911.81
2026	2677492.424	6930.573	32.26496	24010.45
2027	2984596.705	7654.411	35.9325	28382.02
2028	3291700.986	8378.249	39.60005	33026.52
2029	3598805.267	9102.087	43.26759	37943.94
2030	3905909.548	9825.925	46.93513	43134.29
2031	4213013.829	10549.76	50.60267	48597.57
2032	4520118.11	11273.6	54.27021	54333.77

The table clearly demonstrates that the development of new energy vehicles is expected to improve steadily over the next decade, particularly in terms of market share. Additionally, the ownership rate of new energy vehicles is projected to rise significantly.

5. Grey Correlation Analysis

5.1 Application of Grey Correlation in Variable Analysis

Grey Correlation Analysis, derived from grey system theory, is predominantly utilized to determine the correlation levels between multiple variables[10].

First, establish an association sequence. The preprocessed data is sorted to obtain a correlation sequence x_i, $i = 1,2 \cdots n$. A series of associations can be arranged by a specific feature, or by a combination of multiple features.

Second, the correlation coefficient is calculated. The distance between the ranking of each variable and the association sequence is calculated, and the correlation coefficient is obtained:

$$\begin{cases} \Delta_i(k) = |x_0(k) - x_i(k)| \\ \xi_i(k) = \frac{[min\Delta_i(k)+\rho max\Delta_i(k)]}{[\Delta_i(k)+\rho max\Delta_i(k)]}, i = 1,2,\dots n \end{cases} \tag{17}$$

Where is the ρ resolution coefficient, take 0.5; $max\Delta i(k)$ is the maximum value of the two poles; $min\Delta i(k)$ is the minimum value of the two poles.

Again, determine the degree of relevance. Correlation can be used to assess the similarity or correlation between variables. Based on the calculated correlation coefficient, the correlation degree between the variables is calculated.

$$\begin{cases} \gamma_1 = \frac{1}{n}\sum_{k=1}^{n} \xi_i \\ \gamma_1' = \sum_{k=1}^{n} w_i \xi i(k) \end{cases} \qquad i = 1, 2, \dots, n \tag{18}$$

Where is the w_i weight of the indicator.

Finally, analyze the results. Analyze the relationship between variables based on the degree of correlation. Variables with a high degree of correlation indicate that they have strong correlation in grey correlation analysis and can be used as a key variable.

5.2 Model Establishment

5.2.1 Select an Indicator

In order to analyze the impact of new energy electric vehicles on the global traditional energy vehicle industry, this paper collected data from 66 countries, including China, the United States, and the United Kingdom. Data spanning from 2010 to 2023 have been gathered for each of these indicators to facilitate a comprehensive problem analysis.

5.2.2 Trend Forecasting

This paper organizes the collected data by arranging it chronologically and constructs a mixed chart that displays the sales volume and the number of patents of new energy vehicles alongside the production statistics of traditional automobiles across various countries. The results are shown in Fig 3.

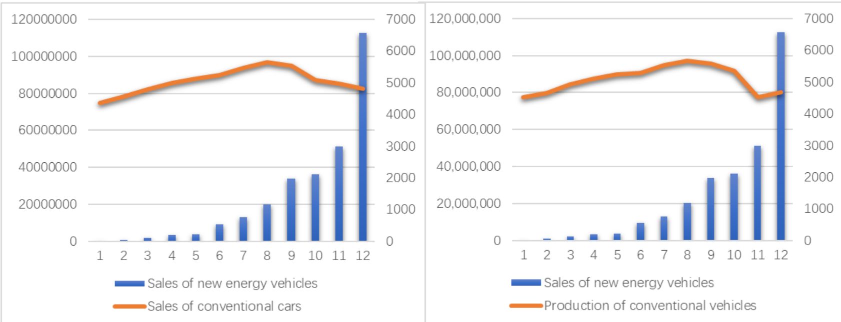

Figure 3: Trend chart

As can be seen from Fig 3, with the gradual increase in the sales of new energy vehicles, the production and sales of traditional vehicles show a trend of first increasing and then decreasing. The possible reason is that at the beginning, new energy vehicles have not yet developed, and the sales volume is small, which has not affected the production and sales of traditional cars. With the passage of time, new energy vehicles have begun to gain momentum and compete with traditional energy vehicles, resulting in a decline in the production and sales of traditional vehicles. At present, traditional cars are still the mainstream, and the future may be the home of new energy vehicles. It is concluded that there is a significant correlation between the production and sales of new energy vehicles and traditional vehicles.

5.2.3 Determine the Number of Series

To deepen our understanding of the impact of new energy electric vehicles on the global traditional energy vehicle industry, this paper conducted a grey correlation analysis. In accordance with grey system theory, this paper categorized the processed data into two sequences: the characteristic sequence and the parent sequence. The characteristic sequence variables include the production statistics of traditional automobiles by country, the number of patents for traditional automobiles, and their sales volumes. Conversely, the parent sequence variable is defined as the total sales volume of new energy vehicles. This analysis helps in identifying how closely the changes in traditional automobile metrics are related to the advancements in new energy vehicle sales.

5.2.4 Count

This paper employed grey correlation analysis to evaluate three specific aspects: the production statistics of traditional automobiles by country, the number of patents for traditional automobiles, and the sales volumes of traditional automobiles. This analysis encompassed 12 data points. This paper sets the resolution coefficient at 0.5 and computes the correlation values. The results of this analysis are visually presented in Fig 4.

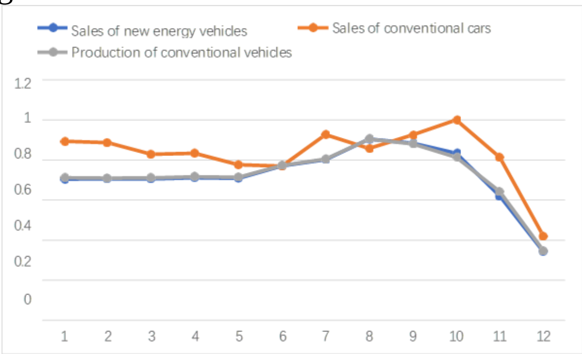

Figure 4: Correlation coefficient graph

Fig 4 illustrates that there is a significant correlation between the sales of new energy vehicles and key metrics of the traditional vehicle industry, including the production rates, the number of patents, and the sales volumes of traditional automobiles.

5.2.5 Permutation

The results of the correlation coefficients were weighted to derive the correlation values for the three evaluation criteria. These values range from 0 to 1, where a higher value indicates a stronger correlation with the reference value (parent sequence). Consequently, a higher correlation value suggests a more significant impact, leading to a higher ranking of the evaluation criteria.

5.3 Analysis of the Results

The final result is shown in Table 5.

Table 5: Correlation Results

Evaluation items	Relevance	Ranking
Number of patents	0.828	1
Conventional car sales	0.729	2
Conventional automobile production	0.725	3

As shown in Table 5, the correlation between the number of patents for traditional automobiles and the sales of new energy vehicles stands at 0.828, ranking highest. This is followed by a correlation of 0.729 between traditional car sales and new energy vehicle sales, which ranks second. The correlation between traditional vehicle production and new energy vehicle sales is slightly lower at 0.725, placing it third. These rankings indicate a strong positive correlation between the number of traditional automobile patents and the sales of new energy vehicles, aligning with our prior assumptions.

The correlation between the production statistics of traditional automobiles and the number of patents across various countries shows comparable strength, which supports our initial hypotheses. The underlying reason for these strong correlations is likely linked to the early-stage improvements in economic living standards, which bolstered the traditional automobile industry and, subsequently, influenced the rise of new energy vehicles. As the market presence of new energy vehicles expanded, competition intensified, leading to a shift from a promotion effect to a suppression effect in the traditional automobile market.

6. Conclusion

The results of the study indicate that the market share of new energy vehicles will steadily increase over the next decade, which indicates that people will shift to a preference for sustainable vehicles. Grey correlation analysis further highlights the interconnected dynamics between the traditional and NEV markets, demonstrating how the rise of NEVs is beginning to impact traditional automotive manufacturing through competitive pressures and innovation incentives. This regression model developed in this study confirms that market dynamics, such as increasing sales of new energy vehicles and expanding market share, are important drivers for the development of the industry. It is clear that NEVs are not just temporary replacements, but pave the way for a more sustainable and technologically advanced automotive landscape.

In conclusion, the future of new energy vehicles is promising, marked by robust growth and increasing relevance in the global market. This study not only aids in understanding the current state and future potential of NEEVs but also assists industry stakeholders in making informed decisions to navigate the challenges and opportunities ahead.

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