Prediction and Evaluation of the Impact of New Energy Electric Vehicles in China Based on Machine Learning

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Abstract. Considering the urgency of environmental issues and the importance of sustainable energy development, accelerating the development of China's new energy electric vehicle sector is an important decision. The study analyzed the expansion of Chinese new energy electric vehicle industry from 2002 to 2022 using entropy weighted TOPSIS method and gradient boosting regression method. The findings suggested that annual GDP and investment in renewable energy were two important contributors for the growth of new energy electric vehicles. Furthermore, this study compared six different machine learning models to determine which model was more appropriate for this study. The results showed that the gradient boosting regression model performed well in the forecasting task of this study. Moreover, this study quantitatively analyzed the impact of new energy electric vehicles on environmental improvement and traditional automobile industry. The analysis found that the introduction of new energy electric vehicles would significantly reduce regional environmental pollution index by 43.5% and lower the conventional vehicle development index by 12.99%. The findings showed that new energy electric vehicles had a great impact on the traditional automobile industry and made a significant contribution to improving the environment.

Keywords: entropy weighted TOPSIS, gradient boosting regression, Machine Learning, New Energy Vehicle, Sustainable Development

1 Introduction

1.1 Background

The growth of new energy vehicles[1,2] has become an international hot topic due to growing environmental protection awareness and changing energy demands. China, the world's largest automobile market, recognizes the importance of promoting new energy vehicles[1,2] to address environmental issues and promote energy transition, and has developed various support measures for this purpose. Against this background, this study aims to analyze and forecast the developing trend of new energy automobile in China and to explore its significant impact of this trend on the overall automotive industry. The role of new energy automobile in environmental protection and sustainable development will also be analyzed.

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1.2 Restatement Problem Analysis

First, the entropy weighted TOPSIS method[3,4] is applied in this study to construct an evaluation model aimed at comprehensively assessing the growth indicators of new energy electric vehicles in China. Second, this study compares six models to determine which model excels at the forecasting task of this study. In addition, this study quantitatively analyzes the possible impacts of new energy electric vehicles on the traditional automotive industry and the specific impacts of widespread urban adoption of new energy electric vehicles on pollution emissions.

2 Materials and Methods

2.1 Datasets

The diffusion of new energy electric vehicles[1,2] was closely related to policies, new energy technologies, infrastructure development, economic factors, citizens' environmental awareness and energy factors. Therefore, this study extracted the following indicators from the above factors to characterize projected growth in new energy electric automobiles from 2002 to 2022: investment in renewable energy, carbon emissions, hydrogen emissions, annual electricity consumption, and annual GDP.

2.2 Modeling and Solution

The study utilized the entropy weighted TOPSIS method[3,4] to conduct a comprehensive evaluation of the development of new energy electric vehicles. Evaluation indicators included the production volume, the sales volume, the vehicle retention volume and market share of new energy automobiles. In this study, given the positive correlation between these indicators and the development of the new energy electric automobile industry, these indicators were set to positive weights. In this study, the value range of the new energy electric vehicle growth score obtained by entropy weighted TOPSIS[3,4] was extended to [0, 10], which helped to reduce the prediction error of the subsequent study. Besides, aiming to quantify the role of each indicator, this study quantitatively evaluated the importance of indicators based on the gradient boosting regression model[5,6]. By gradually reducing the features in the model and recording the error of the gradient boost regression model[5,6] in predicting the growth score of new energy electric vehicles, the error was normalized to determine the importance ranking of each indicator. Additionally, this study constructed and evaluated six different machine learning models, which included Random Forest Regression[5], Gradient Boosting Regression[5,6], Linear Regression[7], Bayesian Regression[8], Decision Tree Regression[9], and Bagging Regression[5]. In order to evaluate the prediction error, this study introduced MAE[10] as an indicator. Due to the small sample size of the dataset, this study introduced the oversampling processing mechanism to extend the dataset based on the unsupervised learning idea. Through oversampling, this study expanded the number of dataset to 100 cases. This study compared these six different machine learning models and concluded that the gradient boosting regression model[5,6] performed outstandingly on the prediction task in this study. In the meantime, this study constructed a model based on gradient boosting regression[5,6] to predict the development indicators of the traditional automobile industry from 2002 to 2022. In this process, weight of each evaluation indicator was determined using the entropy weighted TOPSIS method[3,4]. The selected evaluation indicators included: production volume of traditional automobiles, sales volume of traditional automobiles, number of traditional automobiles, and the proportion of traditional automobiles in the whole automobile market. For quantifying the specific impact of new energy electric vehicles on the conventional automobile sector, the development indicators predicted by the model were compared with the actual observed data. This comparison was based on the premise that realistic data could reflect the real-time impact of new energy electric vehicles on the conventional automobile sector. To quantify degree of this impact, this study compared the actual conventional vehicle development index from 2002 to 2022 with the predicted development index for the same period. The degree of impact was calculated through the formula 1:

$$\mu = \frac{S2 - S1}{S2} \tag{1}$$

The indicator μ measures the possible impact of new energy electric vehicles on the conventional automobile sector by comparing the actual development index with the predicted development index. S1 is an index derived from actual data that reflects the actual development of the conventional automobile sector from 2002 to 2022. S2 represents the predicted conventional automobile development index from 2002 to 2022, which represents the expected development of the conventional automobile sector in the absence of new energy electric vehicles intervening in the market. By comparing S1 and S2, the impact of new energy electric vehicles on the traditional automobile sector can be quantitatively analyzed. If S1 is significantly lower than S2, then μ will show a large positive value, which means that new energy electric vehicles have a significant impact on the traditional automobile industry. If S1 and S2 are close to each other, then the value of μ may be close to zero or small, which means that new energy automobiles have little impact on traditional automobile sector.

In order to assess how new energy electric vehicles can contribute to environmental protection, this study constructed a model based on a city with one million inhabitants. It was assumed that the ratio of new energy electric vehicle used in this city would be the same as the average ratio of new energy electric vehicle used in China in 2022. Furthermore, this study used the average exhaust emissions of all types of new energy electric vehicles from the market to represent emission levels of new energy electric vehicles in the city, and the same methodology was used to define the emissions of conventional fuel vehicles. Meanwhile, this study established a TOPSIS evaluation for emissions, which categorized the degree of pollution from automobile emissions in the city into a single composite score. Also, a gradient boosting regression model[5,6] was used to predict the value of the score without the introduction of new energy vehicles. By comparing the changes in the pollution index before and after the introduction of new energy electric vehicles, the positive impact of new energy electric vehicles on environmental protection was quantified. This method not only ensured the objectivity of the analysis, but also reflected the importance of new energy electric vehicles to the cause of environmental protection.

3 Results

The distribution of the amplified dataset is shown in Figure 1.

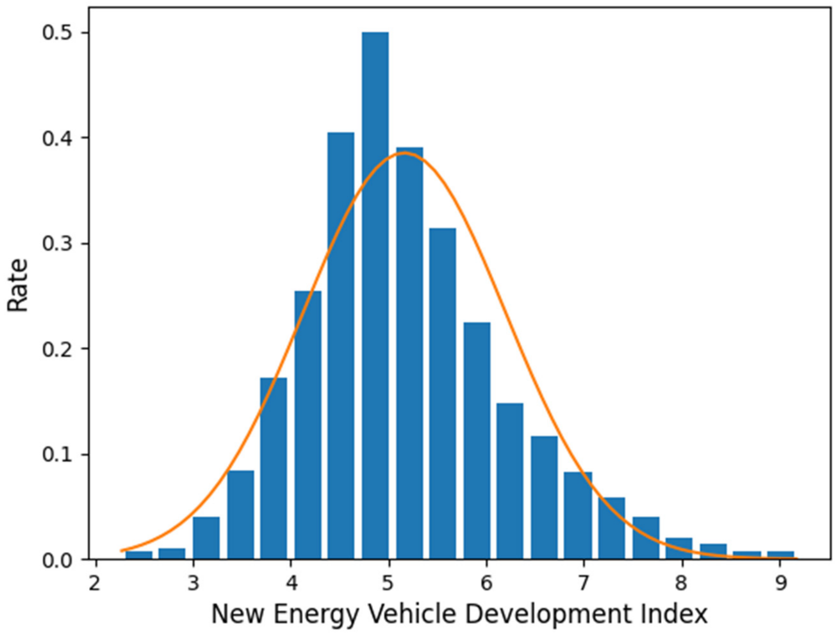

Fig. 1. The distribution of the amplified dataset

The ranking of importance of each feature is shown in Figure 2.

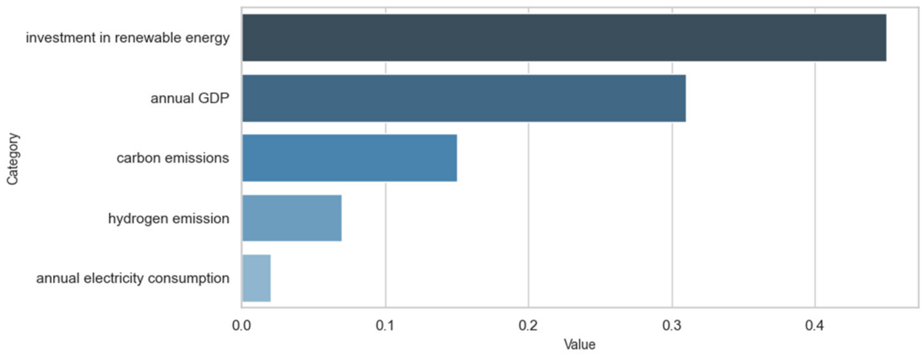

Fig. 2. Importance ranking of factors affecting the growth of new energy electric vehicles

The analysis finds that the economy (annual GDP) and policy support (investment in renewable energy) are important contributors to the growth of new energy electric vehicles.

In this study, the dataset was divided into training set and test set according to 8:2. The results that are obtained for the six models using the preprocessed data are shown in Figure 3.

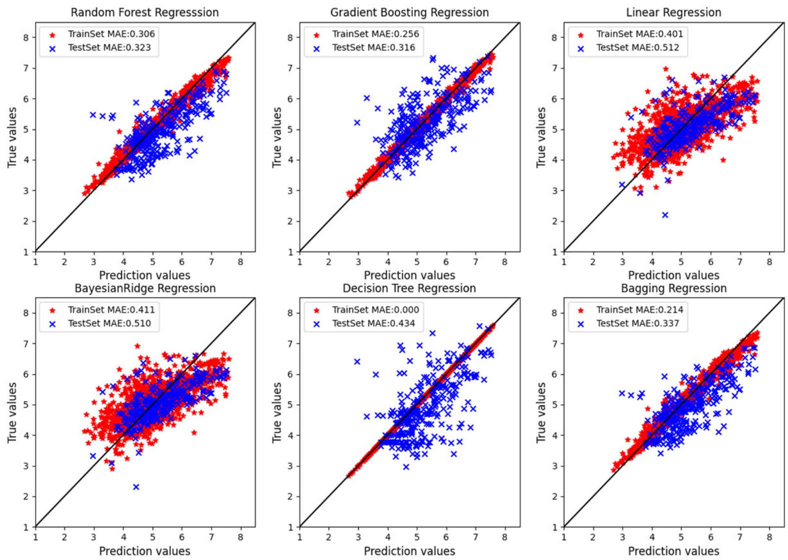

Fig. 3. Prediction errors of six regression models

This graph showed a comparison of the performance of six different regression models. Each model used the same dataset and showed how the models performed on the training set (red section) and the test set (blue section). The diagonal line in the graph represented the prediction in the ideal case, which was the case where the predicted value was exactly equal to the true value. The MAE for the Gradient Boosting Regression model was 0.256 for the train set and 0.316 for the test set. This showed that the gradient boosting regression model performed well in the prediction task of this study.

The results of quantifying the impact of new energy electric vehicles on the growth of conventional vehicles are shown in Table 1.

Table 1. The impact of the introduction of new energy electric vehicles on traditional vehicles

S1	S2	μ
163.5	187.9	12.99%

The value of S1 is 163.5, which indicates the actual development level of the traditional automobile industry with the introduction of new electric vehicles into the market. The value of S2 is 187.9, which indicates the predicted development level of the traditional automobile industry without the intervention of new energy electric vehicles. The value of μ is 12.99%, indicating that the development level of the traditional automobile industry decreases by 12.99% compared to the predicted value due to the involvement of new energy electric vehicles. This result indicates that the market intervention of new energy electric vehicles has a significant impact on the traditional automobile industry.

This study aimed to evaluate the impact of introducing new energy electric vehicles on the local environmental pollution within a specific area. It involved quantifying the pollution levels caused by vehicle emissions before and after the implementation of these vehicles. The results of the study on the rate of change of the pollution level of vehicle exhaust emissions are presented in Table 2.

Table 2. The impact of the introduction of new energy electric vehicles on the environment

local environmental pollution index before introduction	local environmental pollution index after introduction	rate of change in pollution levels from vehicle emissions
9.99	5.64	43.5%

The results show that the introduction of new energy electric vehicles can be clearly seen to have a positive impact on the environment. After the introduction of new energy electric vehicles, the local environmental pollution index decreased from 9.99 to 5.64, showing significant environmental improvement. At the same time, the rate of change in vehicle emission pollution levels reached 43.5%, which further confirms the significant effect of new energy electric vehicles in reducing tailpipe emissions and improving air quality.

4 Conclusions

This study utilized a machine learning model to predict the impact of the growth of new energy electric vehicles on the traditional automobile industry in China as well as the impact of the introduction of new energy electric vehicles on the regional environment. It was found that new energy electric vehicles significantly reduced the conventional vehicle development index and regional environmental pollution index. In addition, economy and policy support factors were key factors in the development of new energy electric vehicles, emphasizing the role of the government in promoting energy transition and environmental improvement. Considering environmental protection and sustainable development, and the contribution of new energy electric vehicles to environmental protection and the promotion of sustainable development, the new energy electric vehicle industry should continue to be assisted in its further development.

References

[1] Yu R, Cong L, Hui Y, et al. Life cycle CO2 emissions for the new energy vehicles in China drawing on the reshaped survival pattern [J].Science of the Total Environment, 2022:826.

[2] Zhao X, Wang S, Wang X. Characteristics and Trends of Research on New Energy Vehicle Reliability Based on the Web of Science[J].Sustainability, 2018, 10.DOI:10.3390/su10103560.

[3] Lin B, Zhou Y. Measuring the green economic growth in China: Influencing factors and policy perspectives [J]. Energy, 2022(Feb.15):241.

[4] Muqeem M, Sherwani A F, Ahmad M, et al. Application of the Taguchi based entropy weighted TOPSIS method for optimisation of diesel engine performance and emission parameters [J]. International Journal of Heavy Vehicle Systems, 2019, 26(1):69.DOI:10.1504/IJHVS.2019.097111.

[5] Li C, Hao H , Xu B, et al. Improved physics-based structural descriptors of perovskite materials enable higher accuracy of machine learning [J].Computational Materials Science, 2021(198-). DOI:10.1016/j.commatsci.2021.110714.
[6] He J, Wang L , Zhang C, et al. A high throughput screening model of solidophilic flotation reagents for chalcopyrite based on quantum chemistry calculations and machine learning [J]. Minerals Engineering, 2022, 177:107375-.
[7] Zhang J, Wang P , Zhang N .Distribution Network Admittance Matrix Estimation with Linear Regression [J]. IEEE Transactions on Power Systems, 2021, PP(99). DOI:10.1109/TPWRS.2021.3090250.
[8] Moghadam R E, Shafieefar M , Akbari H .A probabilistic approach to predict wave force on a caisson breakwater based on Bayesian regression and experimental data[J].Ocean engineering, 2022(249-Apr.1).DOI:10.1016/j.oceaneng.2022.110945.
[9] Xu M, Watanachaturaporn P, Varshney P K, et al. Decision tree regression for soft classification of remote sensing data [J]. Remote Sensing of Environment, 2005, 97(3):322-336. DOI:10.1016/j.rse.2005.05.008.
[10] Liao Y, Wang Z, Chen X, et al. Fast simulation and prediction of urban pluvial floods using a deep convolutional neural network model [J]. Journal of Hydrology, 2023:624.