Harnessing Regression Analysis and Machine Learning to Unveil the Market Dynamics and Environmental Impact of New Energy Vehicles

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Abstract. This study leverages regression analysis and machine learning algorithms to systematically investigate the growth patterns of the global New Energy Vehicle (NEV) market, evaluate the effects of international policy frameworks on NEVs, and quantify the environmental advantages of NEVs in urban settings. Through the analysis of worldwide market data, case studies on international policies, and urban air quality metrics, this research delineates the pivotal contributions of NEVs to mitigating urban pollution and advancing environmental sustainability. The findings provide empirical evidence and strategic recommendations for policymakers, the automotive industry, and environmental organizations, aimed at promoting the sustainable development of the global NEV market.

Keywords: Logistic regression model, χ^2 test, Multicollinearity analysis.

1. Introduction

Amidst escalating concerns over environmental degradation and the pursuit of sustainable transportation solutions, New Energy Vehicles (NEVs) have emerged as crucial components in this transformative era. Alanazi[1] delves into the merits, challenges, and viable solutions for the broad adaptation of electric vehicles, offering significant insights for the advancement of NEVs. Concurrently, the US Department of Energy[2] highlights the environmental advantages of electric vehicles and their role in diminishing reliance on fossil fuels. Hasan and Islam[3] provide an in-depth analysis of NEVs from both market and environmental standpoints, examining market trends and environmental impacts. While prior studies have explored the market potential and environmental benefits of NEVs, this investigation employs sophisticated analytical methods, such as ridge regression and K-nearest neighbors (KNN), to furnish a more comprehensive outlook. This analysis not only scrutinizes the growth patterns of the global NEV market but also assesses the distinct effects of international policies on this sector, quantifying NEVs' efficacy in enhancing urban air quality. Moreover, this investigation provides essential insights that are instrumental in directing global policy and industry practices towards augmented sustainability.

2. Model Application and Analysis

2.1. Detailed Analysis of Global NEV Market Trends

The evolution of the global New Energy Vehicle (NEV) market was explored through the application of an advanced ridge regression model, chosen for its superior ability to address multicollinearity among predictors. This condition, characterized by high correlations between independent variables, frequently occurs in complex datasets typical of global markets[4]. Ridge regression, notable for its regularization parameter λ, effectively reduces the coefficients of less significant predictors, thereby mitigating the risk of overfitting and enhancing the model’s predictive accuracy[5-6]. Fig 1 depicts the probability density distribution for each feature, providing a foundational understanding of the data characteristics across various values. Subsequently, Fig 2 visualizes the correlation among different features, offering insights into the interrelationships among variables. This visualization aids in comprehending how various factors interact to influence NEV market dynamics.

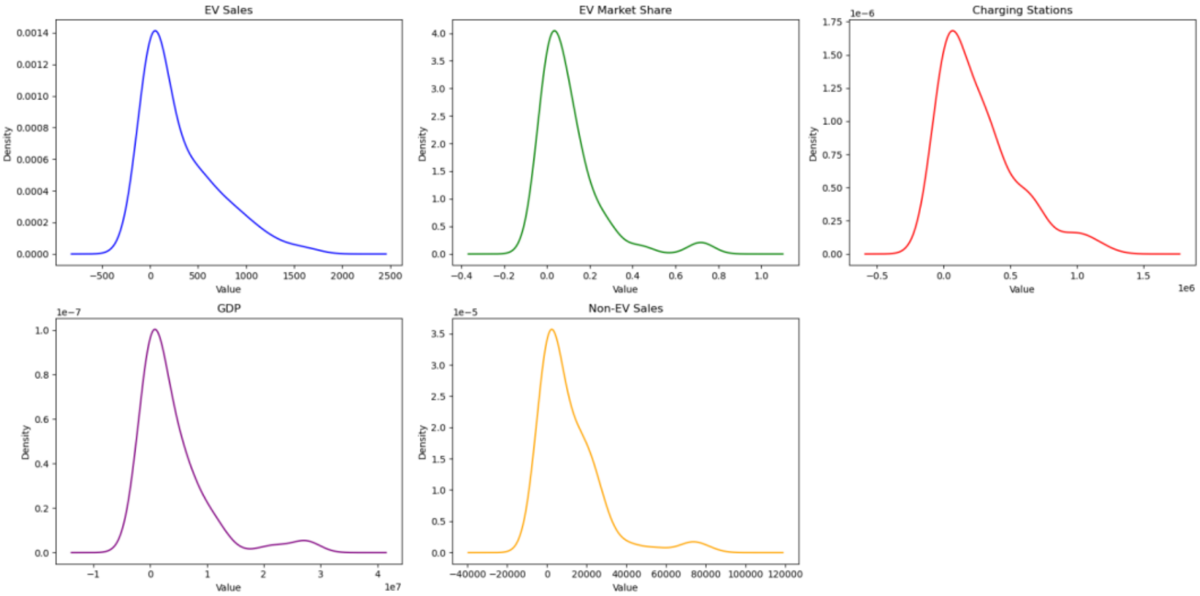

Fig 1. This graph illustrates the probability density distribution of each feature.

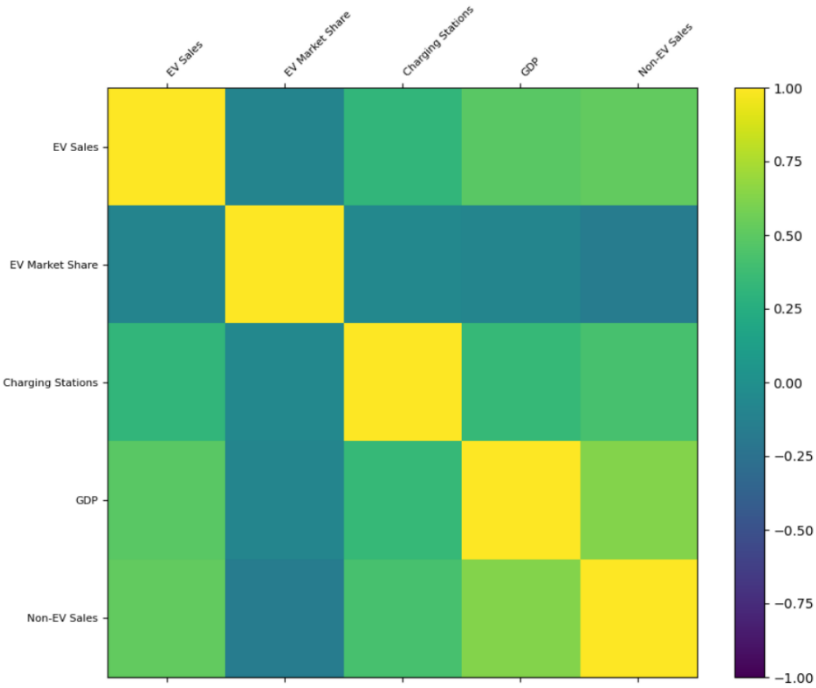

Fig 2. Shows feature correlations, revealing their interconnections

The dataset compiled for this analysis was extensive, incorporating variables such as electric vehicle (EV) sales, market shares, gross domestic product (GDP), the density of charging infrastructure, and governmental incentives across various countries[7-8]. This comprehensive approach enabled the construction of a multifaceted picture of the factors driving NEV adoption and market growth. The ridge regression analysis illuminated the nuanced influence of economic, infrastructural, and policy-related variables on NEV market dynamics, providing a sophisticated model that accounts for the complexity of global market interactions[9-11]. Lastly, Fig 3 presents boxplots of the R-squared values for each model. These boxplots offer an intuitive comparison of the efficacy of different models in explaining the variability in the data, further validating the selected ridge regression model's applicability and effectiveness in analyzing the trends in the global NEV market.

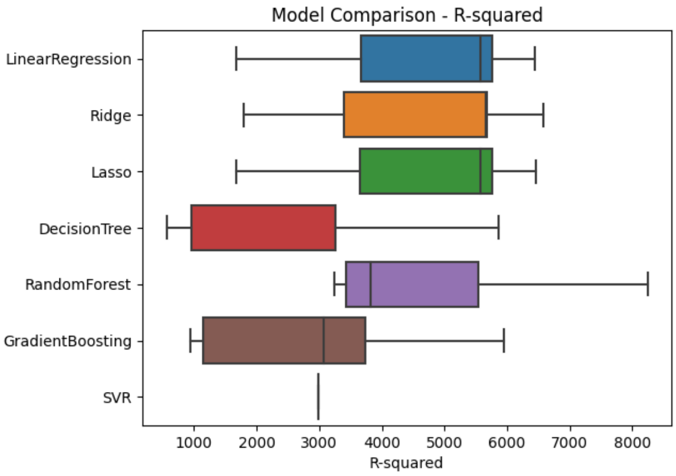

Fig 3. Boxplots of R-squared for Each Model

2.2. Assessing the Impact of International Resistance Policies via KNN Regression

The effects of international resistance policies on the Chinese New Energy Vehicle (NEV) market were evaluated using the K-nearest neighbors (KNN) regression model[12-13]. This non-parametric method was chosen for its adaptability in capturing complex, non-linear relationships without necessitating a predefined equation form[14]. The principle underlying the KNN approach is that similar input features are likely to produce similar output responses, rendering it particularly effective for examining the intricate effects of varied policy environments on NEV sales and market share[15]. Fig 4 employs paired plots to graphically represent and scrutinize the interrelations among variables within the dataset, providing a clear visual analysis of how different factors interact and influence each other.

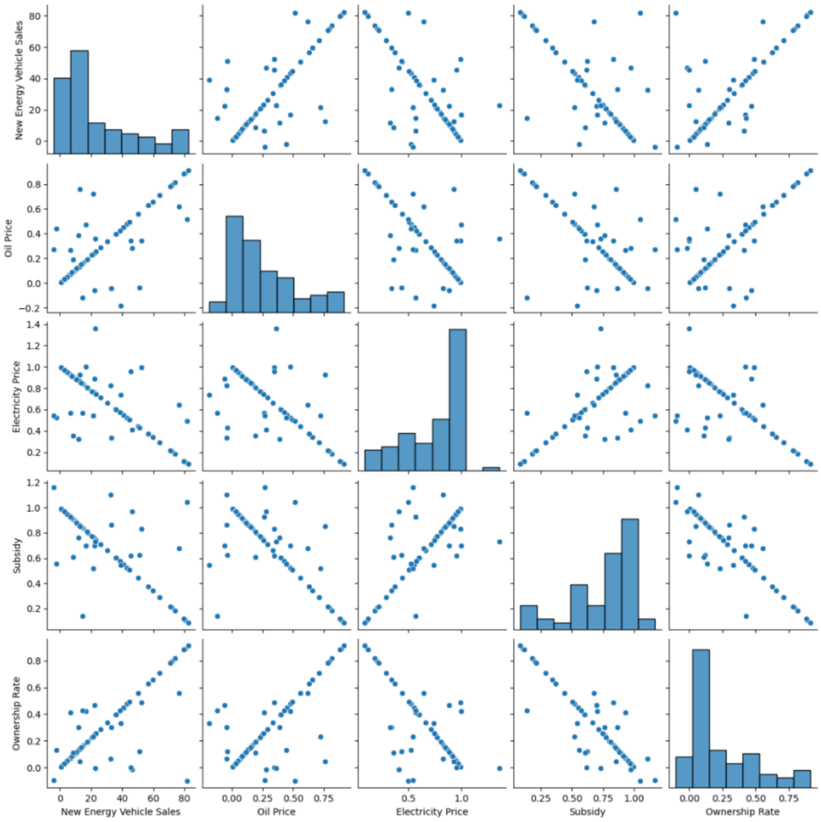

Fig 4. Displays variable relationships with paired plots.

Incorporating a dataset enriched with variables such as import restrictions, tariffs, technical standards, and other forms of policy-induced market barriers, the KNN model facilitated an in-depth examination of the correlation between these factors and the market performance of Chinese New Energy Vehicles (NEVs)[16-17]. The analysis yielded actionable insights into the strategic adjustments required to navigate the policy landscape effectively, underscoring the efficacy of the KNN model in discerning patterns within multidimensional datasets and its pivotal role in strategic decision-making processes. Fig 5 zeroes in on performance by utilizing only the most significant features as determined through feature importance analysis, focusing the analysis on the variables most impactful to NEV market dynamics.

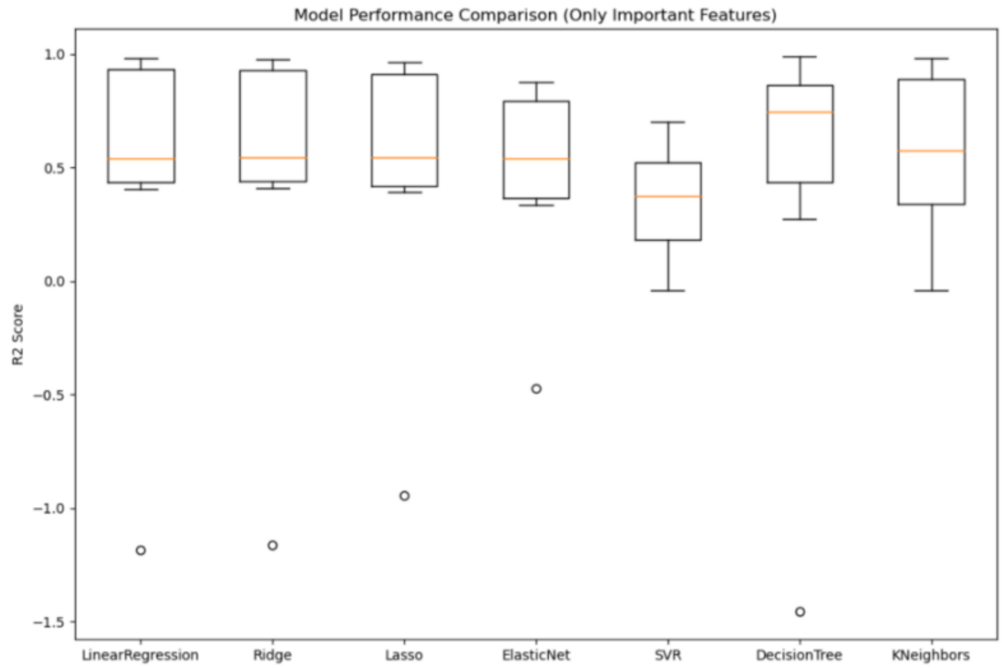

Fig 5. Focus on performance using only the most important features identified through feature importance analysis.

This structured approach, leveraging the KNN regression model, not only elucidates the direct effects of international policies on the Chinese NEV market but also underscores the importance of strategic adaptation in response to policy changes. Fig 4 and 5, enhance the narrative by providing empirical evidence of the relationships between policy variables and market outcomes, and by pinpointing the key drivers of NEV market success.

2.3. Linear Regression Analysis of NEVs' Ecological Impact in Urban Environments

In the analytical portion of this investigation, a sophisticated methodology was deployed to ascertain the environmental repercussions of New Energy Vehicles (NEVs) within urban milieus. This assessment was anchored in the deployment of meticulously defined mathematical models, aimed at quantifying the nexus between NEV adoption metrics and the resultant ameliorations in air quality indices[18]. The models operationalized encompass:

$$E_{ICE} = V_{ICE} \times D \times F \times C \tag{1}$$

$$E_{NEV} = V_{NEV} \times E_{ICE} \tag{2}$$

$$\Delta PM_{2.5} = f(E_{NEV}) \tag{3}$$

wherein, prior to amalgamating the insights gleaned from equations (1) through (3), an elucidation of the variables therein is imperative. Specifically, equation (1) delineates the annual CO2 emissions from conventional vehicles, with E_{ICE} symbolizing the emissions in kilograms, V_{ICE} the vehicle count, D their annual mileage, F denoting average fuel consumption in liters per 100 kilometers, and C representing the CO_2 emission coefficient from gasoline combustion, typically 2.3 kg CO_2 per liter. Equation (2) is designated to calculate the emissions offset by NEVs, where E_{NEV} reflects the reduction in emissions in kilograms, and V_{NEV} quantifies the NEV fleet size. Conclusively, equation (3) articulates the diminution in PM2.5 concentration attributable to NEV integration, with $\Delta PM_{2.5}$ indicating the reduction in particulate matter concentration in micrograms per cubic meter.

Utilizing these equations, based on foundational assumptions and empirical data regarding vehicle ownership dynamics, annual mileage[19], fuel consumption patterns, and CO2 emission coefficients, allows for a detailed comparison of the environmental impacts of traditional vehicles versus NEVs[20]. The results of the linear regression analysis, featuring a slope of -2.303×10^{-9} and an intercept of 33.892, provide significant insights into the effects of increased NEV ownership on reducing PM2.5 concentrations. This comprehensive modeling approach conclusively affirms the considerable environmental benefits conferred by NEVs, highlighting their vital role in improving urban air quality and promoting sustainable urban development practices. Fig 6 illustrates a consistent relationship between emissions reductions and PM2.5 decreases, emphasizing the continuous influence of new energy vehicles on air quality enhancement, irrespective of fluctuations in their numbers. This figure serves as empirical evidence of the positive environmental impact NEVs have, reinforcing the findings from the linear regression analysis and the broader study's conclusions on the pivotal role of NEVs in environmental sustainability efforts.

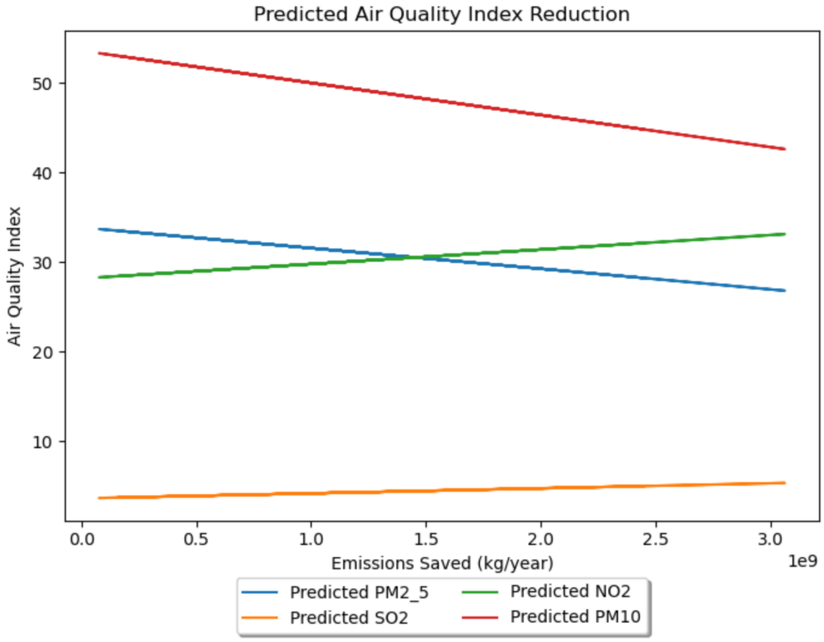

Fig 6. Shows the consistent impact of NEVs on reducing PM2.5, underscoring their role in air quality enhancement.

2.4. Method analysis

Rigorous statistical models were utilized to investigate the dynamics of the New Energy Vehicle (NEV) market, the implications of international policies, and the ecological impacts of NEVs. The deployment of ridge regression, KNN regression, and linear regression facilitated a detailed examination of global trends, policy influences, and environmental benefits, respectively. These methodologies elucidated significant insights into the barriers to NEV adoption and their advantages, highlighting the pivotal role of NEVs in enhancing urban environmental quality. Subsequent visualizations will further underscore these findings, accentuating the importance of NEVs in the context of sustainable urban development.

3. Conclusion

In summary, this study systematically explores the complex landscape of new energy vehicles (NEVs), including global market trends, the impact of international resistance policies, and the ecological contributions of NEVs in urban environments. By applying ridge regression, K-nearest neighbor regression, and linear regression models, we reveal key insights into the drivers of NEV adoption, challenges posed by international policy, and measurable environmental benefits.

The findings highlight the critical role of new energy vehicles in promoting sustainable transportation, mitigating urban air pollution, and contributing to mitigating global climate change. Analysis of international policy implications provides a roadmap for addressing geopolitical dynamics affecting the new energy vehicle market. Furthermore, the environmental benefits identified argue for greater adoption of new energy vehicles as part of urban environmental management strategies.

Policymakers, industry stakeholders, and environmental advocates can refer to these insights to promote NEV adoption through supportive policies, infrastructure development, and awareness campaigns. This study contributes to the sustainable transportation discussion and lays the foundation for future research in the growing field of new energy vehicles, highlighting the importance of technology, policy, and environmental management.

References

[1] Alanazi F. Electric Vehicles: Benefits, Challenges, and Potential Solutions for Widespread Adaptation[J]. Applied Sciences, 2023, 13(10): 6016.

[2] Center A F D. Electric Vehicle Benefits and Considerations[J]. US Department of Energy,[Online]. Available: https://afdc. energy. gov/fuels/electricity_benefits. html.[Accessed 1 March 2023], 2020.

[3] Hasan F, Islam M R. New Energy Vehicles from the Perspective of Market and Environment[J]. Journal of Business Strategy Finance and Management, 2022, 4(1): 38.

[4] Guan Q, Ma Y, Yang S. Sale Forecast and Analysis of Public's Attitude of EV Base on Combination of BP and LSTM Network and Decision Tree[C]//2022 International Conference on Machine Learning and Intelligent Systems Engineering (MLISE). IEEE, 2022: 46-51.

[5] Tang L, Sun J. Predict the sales of New-energy Vehicle using linear regression analysis[C]//E3S Web of Conferences. EDP Sciences, 2019, 118: 02076.

[6] Zheng Y, Ge Y, Muhsen S, et al. New ridge regression, artificial neural networks and support vector machine for wind speed prediction[J]. Advances in Engineering Software, 2023, 179: 103426.

[7] Ledna C, Muratori M, Brooker A, et al. How to support EV adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in California[J]. Energy Policy, 2022, 165: 112931.

[8] Ling Z, Cherry C R, Wen Y. Determining the Factors That Influence Electric Vehicle Adoption: A Stated Preference Survey Study in Bei**g, China[J]. Sustainability, 2021, 13(21): 11719.

[9] Xue C, Zhou H, Wu Q, et al. Impact of incentive policies and other socio-economic factors on electric vehicle market share: A panel data analysis from the 20 countries[J]. Sustainability, 2021, 13(5): 2928.

[10] Wu Y, Yang L, Tian X, et al. Temporal and spatial analysis for end-of-life power batteries from electric vehicles in China[J]. Resources, Conservation and Recycling, 2020, 155: 104651.

[11] Itani K, De Bernardinis A. Review on New-Generation Batteries Technologies: Trends and Future Directions[J]. Energies, 2023, 16(22): 7530.

[12] Zeng B, Li H, Mao C, et al. Modeling, prediction and analysis of new energy vehicle sales in China using a variable-structure grey model[J]. Expert Systems with Applications, 2023, 213: 118879.

[13] Prasad D, Goyal S K, Sharma A, et al. System model for prediction analytics using k-nearest neighbors algorithm[J]. Journal of Computational and Theoretical Nanoscience, 2019, 16(10): 4425-4430.

[14] Afandizadeh S, Sharifi D, Kalantari N, et al. Using machine learning methods to predict electric vehicles penetration in the automotive market[J]. Scientific Reports, 2023, 13(1): 8345.

[15] Saeed M A, M El-kenawy E S, Ibrahim A, et al. A novel voting classifier for electric vehicles population at different locations using Al-Biruni earth radius optimization algorithm[J]. Frontiers in Energy Research, 2023, 11: 1221032.

[16] Liu X, **e F, Wang H, et al. The impact of policy mixes on new energy vehicle diffusion in China[J]. Clean Technologies and Environmental Policy, 2021, 23: 1457-1474.

[17] Wang D, Li Y. Measuring the policy effectiveness of China's new-energy vehicle industry and its differential impact on supply and demand markets[J]. Sustainability, 2022, 14(13): 8215.

[18] Brozynski M T, Leibowicz B D. Decarbonizing power and transportation at the urban scale: An analysis of the Austin, Texas Community Climate Plan[J]. Sustainable cities and society, 2018, 43: 41-54.

[19] Requia W J, Mohamed M, Higgins C D, et al. How clean are electric vehicles? Evidence-based review of the effects of electric mobility on air pollutants, greenhouse gas emissions and human health[J]. Atmospheric Environment, 2018, 185: 64-77.

[20] Moseman A, Paltsev S. Are electric vehicles definitely better for the climate than gas-powered cars[J]. 2022.