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Research on the Future Development of New Energy Power Vehicles Based on Python

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Abstract

Countries need to promote and study the development trends of new energy-electric vehicles in response to global climate issues. In this study, principal component analysis and cumulative contribution rate method were used to identify the main factors involved. Regression analysis was performed and the impact of the main factors on the development of new energy vehicles in China were highlighted through the coefficients of the regression analysis. A multivariate environment was established to influence the evaluation model. The system dynamics model was used to simulate the relationship between factors such as penetration rate, energy conservation, and urban environmental quality. It was concluded that the popularization of new energy-electric vehicles has a positive impact on the urban environment. The advantages and disadvantages of the constructed model were also analyzed, where results showed that the constructed model had high precision and accuracy.

Keywords

New energy electric vehicle

Principal component analysis development tendency

ARIMA model

System dynamics model

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1. Introduction

1.1. Problem background

With the advancement of science and technology, global environmental problems and energy crises have become increasingly prominent [1]. Nations all over the world have taken measures to actively deal with the crisis, thus ensuring the country's sound economic and social development [2]. Not only do cars emit carbon dioxide that contributes to the greenhouse effect but they also consume large amounts of petroleum. All countries are actively taking innovative measures to counter these issues posed by the continuous development of the automobile industry [3]. The building sector has emerged as the primary contributor to greenhouse gas emissions on a global scale, accounting for approximately 36% of the total terminal energy consumption and 40% of the total carbon emissions [4–6]. In 2018, the building sector in China alone produced a staggering 4.93 billion tons of carbon emissions, constituting 51.3% of the nation's total carbon emissions. Nevertheless, it is worth noting that the building sector holds immense potential for energy conservation, with the capacity to contribute up to 56% of carbon reduction by 2050. In 2019, Beijing's building sector accounted for 53.8% of the city's total carbon emissions, surpassing the national average [7–10]. From the perspective of replacing fuel and gasoline with other energy sources, it can be predicted that new energy vehicles will completely replace fuel-powered vehicles in the future [1]. The introduction of new energy vehicles not only reduces carbon emissions but also decarbonizes the entire economic system by decreasing carbon intensity [11]. The development of new energy vehicles has thus become the consensus of the international community.

New energy vehicles, primarily electric vehicles, use on-board power as the driving force and electric motors to operate the vehicle, which not only meets the needs of urban vehicles but also reduces pollution and lessens the impact on the environment [12]. A high fuel cost leads to an increase in driving costs. Hence, consumers are more inclined to purchase new energy vehicles, which are more cost-effective due to the omission of fuel, and achieve the purpose of improving air quality [13].

The Chinese government has outlined plans for developing new energy vehicles (NEVs) to achieve energy conservation and carbon dioxide emission reduction [14]. One purpose of stimulating the NEVs through the "Internet+" initiative is to promote the diversification of vehicle energy systems, advance industrial upgrading, and transformation [15]. The NEV industry has achieved great development and has gradually become another Chinese symbol following the development of China's high-speed rail.

2. Data description

2.1. Data collection

To predict the development of NEVs in China in the next 10 years, it is necessary to obtain a collection of previously relevant data. Through the official publishing platform or the National Bureau of Statistics and other institutions, data was obtained and screened to ensure its accuracy and authenticity. All data related to the development trend of NEVs in China during the inquiry process were recorded and compiled for reference. The collected data was then used to establish a model in later stages.

3. Model building and solutions

3.1. Principal component analysis

To solve the first problem, it is necessary to observe the data containing multiple variables, collect a large amount of data, and carry out data analysis [16]. Principal component analysis can be used to solve this problem. Not only does this reduce the indicators to be analyzed but it also reduces the loss of information within the original indicators to achieve a comprehensive analysis of the collected data. In statistics, principal component analysis aims to simplify multiple indicators into a smaller set using the idea of dimensionality reduction. With this, significant reductions in time and cost can be achieved. Principal component analysis is a linear transformation. This refers to the transformation of data into a new coordinate system in which the first variance of any data projection falls on the first coordinate (first major component), and the second largest variance falls on the second coordinate (second major component), and so on. Principal component analysis is often used to reduce the dimensionality of a data set while preserving the features that contribute the most to the variance of the data set. This is done by retaining the lower-order primary components and ignoring the higher-order primary components, as lower-order components tend to retain the most important aspects of the data.

3.1.1. Standardization of raw data

$$\bar{x}_j = \frac{1}{n}\sum_{i=1}^{n} x_{ij} \tag{1}$$

$$var\,(x_j) = \frac{1}{n-1}\sum_{i=1}^{n} (x_{ij} - \bar{x}_j)^2 \; (j = 1,2,\cdots,p) \tag{2}$$

$$x_{ij}^{*} = \frac{x_{ij} - \bar{x}_j}{\sqrt{var\,(x_j)}} \; (i = 1,2,\cdots,n; j = 1,2,\cdots,\ p) \tag{3}$$

3.1.2. Calculation of the correlation coefficient matrix

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \vdots & \cdots & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix} \tag{4}$$

For convenience, it is assumed that the original data is still represented by X after normalization, so the correlation coefficient of the data after standardization is:

$$r_{ij} = \frac{1}{n-1}\sum_{t=1}^{n} x_{ti}\, x_{tj} (i, j = 1,2,\cdots,p) \quad (5)$$

By using Jacobi's method, the eigenvalues of the correlation coefficient matrix R can be obtained, and the corresponding eigenvector $b_i = (b_{i1}, bi_2 \ldots b_{ip})$, i=1,2…p.

3.2. Analysis of regression

Regression analysis is used to determine the interdependent quantitative relationship between two or more variables [17]. It is a predictive modeling technique that analyzes specific forms of correlation between two or more phenomena, determines their causal relationships, and uses mathematical modeling to illustrate their specific relationships. Based on this, the relationship between the dependent variable (target) and the independent variable (predictor) is studied. This technique is commonly used for predictive analysis, time series modeling, and discovering causal relationships between variables. Regression analysis can be divided into two methods according to the number of variables involved: single regression and multiple regression analysis. Multiple regression analysis was used in this study [18].

3.3. Multiple regression analysis

Multiple regression analysis refers to treating one of the relevant variables as the dependent variable and one or more of the other variables as the independent variable. A linear or nonlinear mathematical model quantity relationship between multiple variables is then established, and sample data is used for analysis. The idea of linear regression is included in other multivariate analyses, where regression aims to approach the average. For a linear regression equation, the more variables it includes, the more likely it is to reflect real problems. The main purpose of multiple linear regression analysis is to interpret data and predict a possibility for future development. Therefore, the solution for problem 1 is to establish a multiple regression analysis model with the following equation:

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \cdots + \beta_m x_m + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \end{cases} \quad (6)$$

Where, β_0, β_1, …, β_m is the regression coefficient and ε is the error term.

3.4. Specific steps for data analysis

(1) Step 1

Firstly, the collected annual sales data of NEVs were visually processed using a simulation program of Python software. To facilitate calculation, the collected data are first calculated in a unified unit. The data was then processed to calculate the annual sales. The plot.surface function in Python software was used to simulate the growth value of the annual sales volume NEVs.

(2) Step 2

Based on the requirements of the problem, it is necessary to analyze the influence of major factors on the development of NEVs in China. This was done through the simulation program of Python software to simulate and develop a corresponding data chart of the annual sales growth of NEVs. This way, a line chart illustrating the sales growth of NEVs every year was obtained. From the line chart, the trend of the annual sales volume of NEVs from 2015 to 2023 can be observed. The impact of the main factors affecting the development of NEVs in China was observed by comparing relevant data and drawing objective conclusions. This further indicates that comparing analysis results can develop more convincing arguments.

(3) Step 3

According to the line chart of the annual sales growth of NEVs, correlation analysis was performed on the collected data related to NEVs and the main factors affecting the development of NEVs.

3.5. Model solution

The data processing method of the principal component analysis can be adapted to perform data analysis on the collected data. It can be concluded from the analysis that the main influencing variables of new energy vehicles included four factors: government factors (government subsidies, the intensity of government support, etc.), market factors (consumer demand, market acceptance, etc.), technical factors (battery technology, vehicle capability, etc.), and environmental factors (environmental protection awareness, pollution, etc.).

Analysis of subsidies corresponding to different mileages of different types of NEVs by the government has revealed that the subsidy policies evolved. Then, the plot.surface function in Python software is used to simulate the changes of said policies on the different mileage of different types of NEV.

To increase the reliability and authenticity of the results of the analysis, it is necessary to conduct a more comprehensive and objective analysis of battery technology. Through comprehensive and multi-angle analysis of collected data, the different influences of different types of batteries on the sales volume of NEVs can be obtained.

Through objective analysis of the four main factors that affected the sales volume of new energy electric vehicles mentioned above, it is assumed that there exists a certain linear relationship. Therefore, the following multivariate regression analysis equation expression can be established for these main factors:

$$\begin{cases} y = \beta_0 + \beta_1 x_1 + \beta_3 x_3 + \beta_4 x_4 + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \end{cases} \tag{7}$$

The Pearson correlation coefficient is widely used to measure the degree of correlation between two variables, with a value between -1 and 1. The sample correlation coefficient refers to the degree of linear correlation between variables in the sample. A value of 1 means that the relationship between two variables can be well described by a linear equation, and all data points fall well on a straight line. One variable increases with the increase of another variable. A coefficient value of -1 means that all data points fall on a straight line and one variable decreases with the increase of another variable, showing a negative correlation. If the value of the coefficient is 0, it means that there is no linear relationship between the two variables. The Pearson correlation coefficient evolved from a similar but slightly different idea proposed by Pearson. This correlation coefficient can also be called the Pearson product-moment correlation coefficient. The Pearson correlation coefficient between two different variables can be defined as the quotient of the covariance and standard deviation between the two variables, which is expressed as the following expression:

$$\rho(x, y) = \frac{cov\,(X,Y)}{\sigma x \sigma y} = \frac{E[(X-\mu x)(Y-\mu y)]}{\sigma x \sigma y} \tag{8}$$

The above expression defines the overall correlation coefficient, using commonly used Greek lowercase letters like ρ as a representative symbol. By estimating the covariance and standard deviation of the sample, the required Pearson correlation coefficient can be obtained, often represented by the lowercase letter r in English:

$$r = \frac{\sum_{i=1}^{n}(X_i-\overline{X})(Y_i-\overline{Y})}{\sqrt{\sum_{i=1}^{n}(X_i-\overline{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i-\overline{Y})^2}} \tag{9}$$

The r value can also be estimated from the mean standard score of the sample data of (X_i, Y_i), resulting in an expression equivalent to the above equation:

$$r = \frac{1}{n-1}\sum_{i=1}^{n}\left(\frac{X_i-\overline{X}}{\sigma x}\right)\left(\frac{Y_i-\overline{Y}}{\sigma y}\right) \tag{10}$$

The Pearson correlation coefficient has an important mathematical characteristic, that is no matter how the position and scale of two variables change, it will not cause a change in the correlation coefficient. In other words, the invariant of its change (determined by the sign). That is to say, if X was moved to a+bX and Y to c+dY, the positions of X and Y do not affect the Pearson correlation coefficients of the two variables. This is true for both the population and sample Pearson correlation coefficients.

3.6. Result analysis

By analyzing data from steps 1–3, we can objectively analyze the Pearson correlation coefficient between the main influencing factors and the sales volume of NEVs, where the correlation coefficient can be directly obtained. The influence factor of the sales volume of NEVs was determined to be -0.5324432452634554, while the technical factor was 0.7173609680682391.

4. Model solution for problem 2

To analyze the impact of the electrification of NEVs (including electric buses) on the ecological environment, it is necessary to establish a multivariate assessment model of NEVs and their environmental impact. The system dynamics model can be used to simulate the complex interaction between the penetration rate of NEVs, pollutant emission reduction, energy reduction, and other factors that affect urban environmental quality.

4.1. System dynamics model

The system dynamics model is a cycle method to simulate the internal interaction and feedback of complex systems. This model usually includes state variables, flow, auxiliary variables, and a feedback cycle.

4.2. Buildup of a model

When establishing a model, it is necessary to first determine the state variables, flow rate, and auxiliary variables. In this study, the urban air quality, the number of NEVs, and carbon emissions were used as state variables. The number of NEVs produced each year and the number of traditional energy vehicles dumped each year were considered as flow rates. At the same time, the average energy consumption and carbon emission coefficient were used as auxiliary variables. Based on this, a system dynamics model was established. This model usually uses differential equations to describe the relationship between variables, as shown below:

New energy electric vehicle growth rate:

$$\frac{d(EV)}{dt} = rEV \tag{11}$$

Among them, EV represents the number of new energy electric vehicles and r represents the growth rate.

The amount of carbon emissions reduction:

$$\Delta co_2 = EF_{IC}IC - EF_{EV}EV \tag{12}$$

In the formula, EFIC and EFEV represent the carbon emission coefficients of traditional energy vehicles and new energy electric vehicles, respectively. IC represents the number of traditional energy vehicles. Air quality improvement amount:

$$AQI = f(co_2, other\_pollu\,tan\,t\,s) \tag{13}$$

AQI is the air quality index, which is a function of CO_2 and other pollutants.

4.3. Result analysis

By using Python to simulate the system dynamics model, and then calculate the annual reduction of exhaust gas emissions and energy consumption difference data. The simulation results show that over time, the number of new energy-electric vehicles shows a stable growth trend, which is consistent with the increasing global focus on reducing carbon emissions and improving energy efficiency. With the increase in the number of new energy electric vehicles, since they have lower carbon emissions than traditional energy vehicles, the overall carbon emissions show a downward trend, which indicates that the popularity of new energy electric vehicles has a positive effect on reducing urban carbon emissions. With the reduction of carbon emissions, air quality will be improved, which is reflected in the reduction of the AQI index, which means that the popularization of new energy electric vehicles may play a positive role in improving the urban environment.

5. Conclusion

The popularization of NEVs may have a positive impact on urban environments, including reducing greenhouse gas emissions and improving air quality. With the continuous advance and increasing popularity of NEV technology, its environmental benefits will gradually become evident. The government and urban planners can accelerate this process by promoting NEVs and their related infrastructure, such as the addition of charging stations. Although the positive impact of new energy electric vehicles on the environment is quite evident, it is also necessary to consider their overall environmental impact throughout their lifecycle, including issues such as battery production and waste disposal. The popularization of NEVs is one of the key factors in the transition towards a more sustainable and environmentally friendly city [19].

Disclosure statement

The authors declare no conflict of interest.

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