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Research on Pathways to Achieve the "Dual Carbon" Goals Driven by New Energy Vehicle Popularization Based on a Multi-Source Data Fusion Model

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Abstract. Amid growing global concerns over greenhouse gas emissions, the adoption of new energy vehicles (for short: NEVs) is a key pathway for China to achieve its "Dual Carbon" goals. Existing research examines NEVs from four main dimensions: life cycle emissions, policy mechanisms, regional impacts, and multi-source data integration. While NEVs have lower life cycle emissions than fuel vehicles, their benefits depend heavily on the power mix. Policy studies highlight the importance of subsidies and infrastructure, while regional analyses reveal spatial spillover effects and scenario-dependent emission reductions. This study employs multi-source data fusion, integrating atmospheric and power system data, to build high-precision carbon monitoring models. Using the Bass diffusion model, grey relational analysis, and consumer survey data, we analyze market trends and decision factors. A multi-objective optimization model, enhanced by particle swarm and genetic algorithms, evaluates policy scenarios under constraints of emissions, cost, and efficiency. Results show NEVs significantly reduce urban emissions, with policy-market synergy crucial for long-term growth. Findings emphasize the need to coordinate innovation, incentives, and public engagement to promote green mobility and inform adaptive, efficient policymaking for China's low-carbon transition.

Keywords: Carbon Emissions; New Energy Vehicles (NEVs); Bass Diffusion Model; Grey Relational Analysis (GRA); Policy Simulation.

1. Introduction

Current studies analyze NEVs through four aspects: 1) lifecycle emissions, 2) policy frameworks, 3) geographical impacts, and 4) multi-source data. Research shows NEVs outperform conventional vehicles in emissions, but benefits depend on electricity sources. Policies highlight financial incentives and charging infrastructure, while regional analyses reveal spatial diffusion effects.This study examines NEV industry development and its carbon reduction mechanisms. Historical adoption data were modeled using the Bass diffusion model to predict market penetration and measure emission reductions. Statistical methods evaluated model accuracy. Consumer preference data from surveys were analyzed via grey relational analysis to identify key variables.For policy simulation, a multi-objective optimization framework was built, incorporating carbon emissions, incentives, and market efficiency. Particle swarm optimization and genetic algorithms solved the optimization, quantifying emission reductions across policy scenarios.

2. The basic fundamental of model

2.1. Bass diffusion model

The Bass diffusion model was proposed by Frank M. Bass in 1969 and is used to describe the diffusion process of new products or technologies in the market [1]. The model dynamically estimates the adoption rate of the product by simulating the interaction between innovators and imitators, combined with the potential capacity of the market, and reflects the temporal evolution of consumer acceptance.

Because it can reveal the dynamic characteristics of marketing promotion and user behavior, the Bass model is widely used in fields such as sales forecasting, market penetration assessment and marketing strategy formulation [2].

The following is the structure of the Bass model:

$$n(t)=p\left[m-N(t)\right]+qN(t)/m\left[m-N(t)\right] \tag{1}$$

$$N(t)=m\left[1-e^{(-(p+g)t)}\right]/\left(1+q/pe^{(-(p+g)t)}\right) \tag{2}$$

$$n(t)=\left(mp(p+q)^{2}e^{(-(p+q)t)}\right)/\left[p+qe^{(-(p+q)t)}\right]^{2} \tag{3}$$

Where n (t) is adopters added at time t, N(t) represents the cumulative adoption volume up to that time, m means potential maximum market size and parameters p and q correspond respectively to the innovation and imitation coefficients, reflecting the adoption behaviors of individuals under autonomy and the influence of others.

Optimized Workflow of the Bass Diffusion Model (Refer to Figure 1):

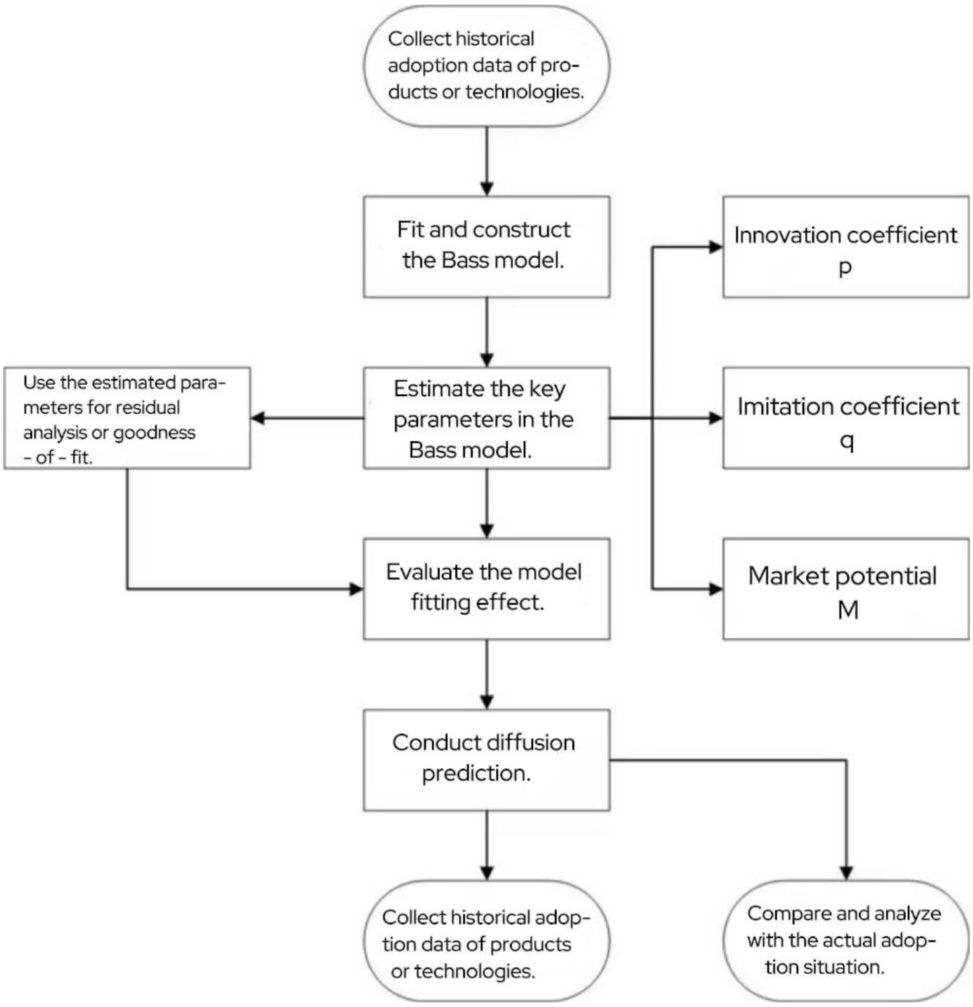

Figure 1. Schematic Workflow of the Bass Diffusion Model

(1) Data Acquisition: Collect historical adoption data (e.g., sales volume, user base).

(2) Model Calibration: Fit the Bass model to the dataset to establish its structural framework.

(3) Parameter Estimation: Derive core parameters:

p: Innovation coefficient (probability of autonomous adoption).

q: Imitation coefficient (probability of adoption influenced by peers).

m: Market potential (maximum adopters).

(4) Model Validation: Assess goodness-of-fit via residual analysis and statistical metrics (e.g., R^2).

(5) Diffusion Forecasting: Project adoption trends using validation datasets or future timeframes.

(6) Predictive Accuracy Evaluation: Compare predictions with empirical outcomes to refine model robustness.

2.2. Grey relational analysis model

Grey relational analysis is an effective method for evaluating the strength of relationships among multiple factors, especially suitable for scenarios with small sample sizes or incomplete information [3]. In the research on public acceptance of new energy vehicles, this method can reveal the correlation strength among various factors and help identify the ones that have the greatest impact on consumers' purchasing decisions. In this study, the public acceptance of new energy vehicles is taken as the mother sequence, while major factors such as policy support, technological progress, economic factors, and social perception are selected as characteristic sequences. By calculating the grey relational degrees between these characteristic sequences and the mother sequence, the influence of each factor on the acceptance of new energy vehicles can be quantitatively analyzed [4].

Figure 2 illustrates the flowchart of the grey relational analysis (GRA) model construction process.

(1) Sequence Definition

Reference Sequence: Public acceptance of new energy vehicles (NEVs).

Comparative Sequences: Key determinants of NEV adoption, including policy incentives, technological advancements, economic feasibility, and social cognition.

(2) Grey Relational Coefficient Calculation

Coefficients are computed using standardized formulae to quantify pairwise correlations between comparative sequences and the reference sequence.

(3) Grey Relational Degree Derivation

Coefficients are aggregated to derive relational degrees, which hierarchically rank the influence intensity of each factor on NEV acceptance.

(4) Critical Factor Identification

Relational degrees are analyzed to identify dominant factors (e.g., social cognition, economic feasibility) and their hierarchical impacts on consumer decision-making.

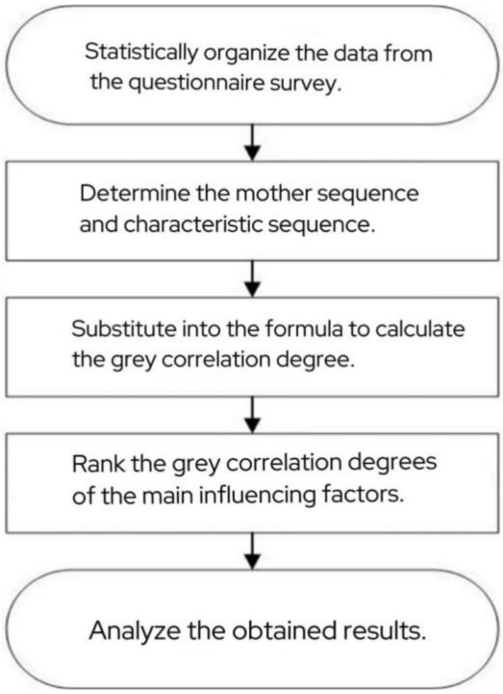

Figure 2. Flowchart of the Grey Relational Analysis (GRA) Model

Grey relational analysis is an effective method for evaluating the strength of relationships among multiple factors, and is particularly suitable for situations with small sample sizes or incomplete information [5]. In the research on the public acceptance of new energy vehicles, the application of this method can reveal the correlation strength among various factors and help identify the factors that have the greatest influence on consumers' car purchase decisions.

According to Formula (4), calculate the correlation coefficients between each characteristic sequence and the parent sequence:

$$yi(k)=\frac{|x0(k)-xi(k)|+\Delta min}{|x0(k)-xi(k)|+\Delta max} \tag{4}$$

Where $x0(k)$ is the value of the parent sequence, $xi(k)$ represents the value of the i-th feature sequence, Δmin and Δmax mean the minimum and maximum difference, respectively.

By calculating the obtained correlation coefficient, the grey correlation degree is further calculated to evaluate the influence of various factors on the public acceptance of new energy vehicles [6]. The formula of grey correlation degree model is Formula (5):

$$\frac{\sum_{k=1}^{n} \gamma i(k)}{n} \tag{5}$$

Where n is the quantity of the samples, $\gamma_i(k)$ denotes the association coefficient between the i-th feature sequence and the parent sequence at the kth time point.

2.3. Multi-objective optimization model

This chapter takes "policy simulation + path optimization" as the main line, constructs a multi-objective optimization model for the development of new energy vehicle industry, and combines Particle Swarm Optimization algorithm (PSO) to solve it, so as to simulate and analyze different policy paths [7].The overall process is shown in Figure 3:

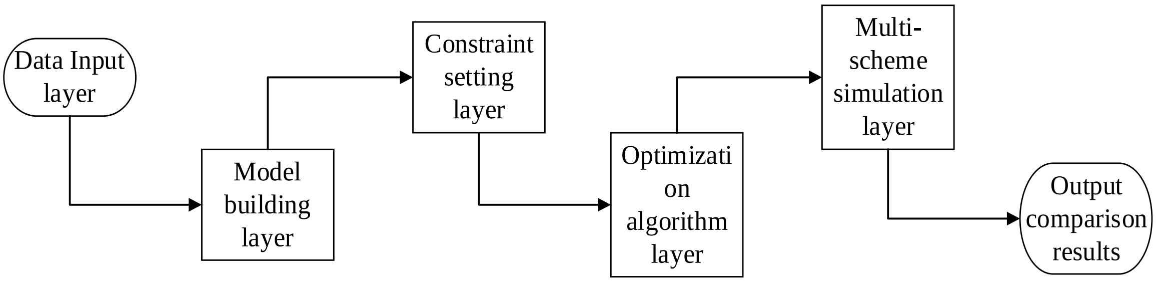

Figure 3. Framework diagram of new energy vehicle industry path optimization and policy simulation research

Data input layer: historical sales volume, carbon emission coefficient, infrastructure investment data, etc.

Model building layer: three main objective functions were constructed: market penetration maximization, carbon emission minimization and infrastructure investment cost minimization.

Constraint setting setting layer: financial budget, resource capacity and other restrictions;

Optimization algorithm layer: particle swarm optimization algorithm or genetic algorithm is used to solve the model.

Result comparison results: The industrial development path and key index comparison maps under different policy programs are output.

In order to realize the multi-dimensional optimization development of the new energy vehicle industry, three main goals are set [8]:

To maximize market penetration (Z_1), see Equation (6):

$$\max Z_1 = \frac{S_{EV}(t)}{S_{TOTAL}(t)} \tag{6}$$

Where $S_{EV}(t)$ is new energy vehicle sales in year t, $S_{TOTAL}(t)$ means total sales volume.

Minimize life cycle carbon emissions (Z_2), see Formula (7):

$$\min Z_2 = \sum_{i=1}^{n} E^i x_i \tag{7}$$

Where E^i represents Unit carbon emissions of Category I NEVs, x_i is its corresponding sales volume

Minimize the infrastructure investment cost (Z_3), see Formula (8):

$$\min Z_3 = \sum_{j=1}^{m} C_j y_j \tag{8}$$

Where C_j represents Unit cost of type j infrastructure, y_j denotes Construction quantity.

The model needs to be optimized under the following policy and resource constraints[9]:

The total constraint of fiscal subsidies is shown in Formula (9):

$$\sum_{i=1}^{n} P_i x_i \leq B \tag{9}$$

Where P_i is the unit subsidy for the first type of vehicle, B means the upper limit of the fiscal budget. Production capacity and sales restrictions are shown in Formula (10):

$$x_i \leq x_i^{\max_{jj}^{\max}} \tag{10}$$

Market penetration logic constraints (such as nonlinear growth fitting), as shown in Formula (11):

$$S_{EV}(t)=S_{EV}(t\text{-}1)+f(P,I,C) \tag{11}$$

3. Results

3.1. Data sources

(1) Data sources of Bass diffusion model

This research is based on the data of China's new energy vehicle market from 2013 to 2024, covering two types of products: pure electric vehicles and hybrid vehicles. The data sources mainly include institutions such as the China Association of Automobile Manufacturers and the National Bureau of Statistics.

(2) Data sources of Grey relational analysis model

The data of this study came from questionnaire surveys of different respondents, and a total of 500 valid questionnaires were collected, with a recovery rate of 96.9%. The content of the questionnaire involves multiple aspects such as gender, age, and main car purchase factors. Specifically, the study focuses on the influence of the following factors: policy support, technological progress, economic factors, social cognition and consumer car purchase budget, etc., and explores their influence on consumers 'decision to purchase new energy vehicles.

3.2. Model study results

(1) Results of Bass diffusion model

On the basis of the aforementioned market diffusion prediction, combined with the carbon emission values of vehicle life cycle of each model unit, this paper estimates the total carbon emission reduction caused by the replacement of traditional fuel vehicles by new energy vehicles year by year in the future. Assuming that the market share of new energy vehicles will gradually expand and completely replace the equivalent number of fuel vehicles, the annual emission reduction can be approximately calculated by the following formula (12):

$$S_{EV}(t)=S_{EV}(t\text{-}1)+f(P,I,C) \tag{12}$$

Where EICE is Unit carbon emissions of internal combustion engine vehicles (39.7 tons), EN EV represents the weighted average carbon emissions of new energy vehicles are calculated by weighting the sales proportions of BEV and HEV.SNEV means the sales volume of new energy vehicles in the current year (unit: ten thousand units)

The obtained results are presented in units of ten thousand tons of CO_2e. New energy vehicles in China in 2025-2035 carbon emissions reductions predicted results are shown in table 1.

Table 1. Forecast of Carbon Reduction from New Energy Vehicles in China from 2025 to 2035

Year	BEV Sales Forecast	HEV Sales Forecast	Weighted average emissions (tons)	Annual emission reduction (10,000 tons of CO_2e)
2025	1557.71	429.17	24.8	2953.7
2026	2222.21	612.24	24.9	4202.5
2027	3000.53	826.68	25	5630
2028	3764.09	1037.04	25	7040.6
2029	4309.25	1187.24	25.1	8020.4
2030	4445.92	1224.9	25.1	8272
2031	4520	1252	25.1	8409.5
2032	4560	1263	25.1	8488.8
2033	4600	1275	25.1	8570
2034	4620	1282	25.1	8611.2
2035	4630	1285	25.1	8631.2

The model prediction results show that the new energy vehicle market will gradually enter the saturation range around 2030, but there is still significant growth space. If new energy vehicles effectively replace traditional fuel vehicles, they can cumulatively reduce nearly 800 million tons of CO_2e carbon emissions between 2025 and 2035, which will play a positive role in promoting the realization of the "dual carbon" goals.

(2) Result of Grey relational analysis model

We conducted grey relational analysis of the data by using Python software, and the results were summarized as shown in Figure 4:

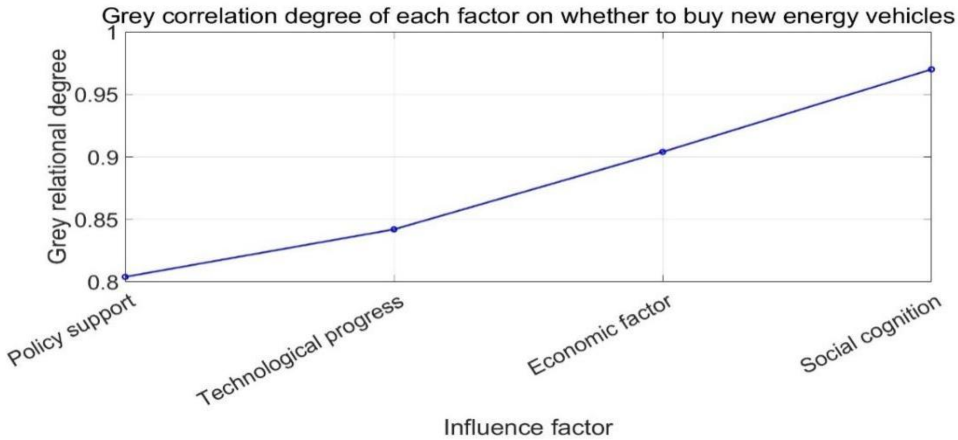

Figure 4. Gray correlation coefficient diagram

The correlation coefficient represents the degree of association between the influencing factors of the sub-sequence (policy support, technological progress, economic factors, social cognition) and whether the parent sequence purchases new energy vehicles. The higher the value, the stronger the degree of association between the characteristic sequence and the parent sequence. The specific results are shown in Table 2:

Table 2. Correlation Degree Results

Factor	Grey Relational Coefficient	Rank
Policy Support	0.804	4
Technological Advancement	0.842	3
Economic Factors	0.904	2
Social Cognition	0.970	1

This study employed grey relational analysis and focused on analyzing various factors influencing consumers' purchase of new energy vehicles. The research results show that policy guidance, technological progress, economic factors and social cognition have all had certain influences on car purchase decisions. In particular, social cognition and economic factors show a relatively high correlation, playing a more significant role in whether consumers choose new energy vehicles. Based on these findings, the government can make decisions in policy formulation and enterprises in the process of market promotion based on more specific and targeted references.

(3) Result of Multi-objective optimization model

This study has designed the following three typical policy scenarios to reflect different policy orientations, as shown in Table 3:

Table 3. Typical Policy Scenario Settings

Scene number	scenario name	Explanation of Policy Characteristics
Plan A	High subsidy and high investment type	Offer purchase subsidies for vehicles, promote infrastructure construction, and increase fiscal investment.
Plan B	Green, low-carbon and stable type	Reduce subsidies, strictly control carbon emissions, and give priority to supporting technological improvements
Plan C	Balanced resource optimization type	Moderate subsidies, with emphasis on the coordinated development of production and sales as well as the harmonious advancement of facilities and technologies.

After normalization processing and weighted analysis, the comprehensive scores of each scheme are shown in Table 4:

Table 4. Comparison of Comprehensive Scores of Different Policy Schemes

Scene number	Market penetration rate score	Carbon emission score	Cost score	Comprehensive Score (weighted)
Plan A	0.92	0.65	0.55	0.73
Plan B	0.68	0.93	0.75	0.78
Plan C	0.80	0.83	0.82	0.82

A three-objective optimization model was constructed, with the objectives covering the maximization of market penetration rate, the minimization of life-cycle carbon emissions, and the minimization of infrastructure investment costs[10]. The particle swarm optimization and genetic algorithm were combined to solve the model, enhancing its efficiency and stability. Three policy scenarios were set up for simulation analysis. The results indicated that the balanced optimization type (Scenario C) performed best in the comprehensive score, achieving a good balance among market expansion, emission reduction benefits, and cost control, demonstrating the comprehensive advantages of a coordinated strategy [11].

4. Conclusion

Combined with multi-objective optimization and intelligent algorithm, this study discusses the path optimization problem of new energy vehicle industry. A three-objective optimization model was proposed to maximize market penetration and minimize carbon emissions and infrastructure costs. Through particle swarm optimization algorithm, different policy scenarios are simulated, and the dynamic impact of policy on industrial development is analyzed.

It is found that the difference of policy mix directly affects the industrial path and carbon emission reduction effect. The "balanced resource optimization type" strategy performs well on multiple objectives, indicating that comprehensive and coordinated policies are crucial for stable industrial growth and low-carbon goals.

Future research can combine game theory and other theories to explore the interaction between government, enterprises and consumers, and analyze the impact of each party's behavior on industrial development. At the same time, we should pay attention to the energy structure, industrial chain coordination and regional differences, promote the comprehensive development of industry in terms of technology, market and environmental governance, and help green transportation and sustainable development.

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