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MULTIDIMENSIONAL DRIVING EFFECTS OF NEW ENERGY VEHICLE MARKET ON GDP GROWTH

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Abstract: In the context of global carbon neutrality and digital economy transformation, the new energy automobile industry has emerged as a pivotal catalyst for restructuring the global energy and industry landscape. However, this rapid growth is accompanied by inherent contradictions, including policy implementation deviations, which hinders its ability to meet the demands of conventional analytical frameworks. In this study, we constructed a multidimensional synergistic evaluation system and analyzed the market dynamics and economic transmission mechanism by using a combination of simulated annealing-moving average-long short-term memory (SA-MA-LSTM) models. The study identified a "threshold effect" in the driving force of industry on gross domestic product (GDP), indicating that infrastructure and supply chains can impede development. The analysis revealed a non-linear relationship between policy and market, emphasizing the necessity for diversified supply strategies. The study proposes the establishment of a dynamic subsidy mechanism, the construction of a technology sharing platform, and other policy insights. These measures will provide an assessment tool for the sustainable development of the industry and contribute to China's experience in economic transformation under global carbon neutrality.
Keywords: New energy vehicle market; SA-MA-LSTM prediction; Policy-Technology-Market synergy framework; GDP driving effect

1 INTRODUCTION

Against global carbon neutrality and digital economic transformation, the new energy vehicle industry drives reshaping the global energy and industrial landscape. China advances it via financial subsidies and double - integral policies, with 2024 market penetration expected at 47.8%, boosting regional growth. However, literature shows three research limitations: Policy impact studies are mostly one - dimensional. Liao Shuimei et al. built a policy intensity index [1], and Ye Zhouzhe analyzed policy synergies with a spatio - temporal tensor model, but both lack a dynamic game framework [2]. Enterprise tech innovation assessment leans toward patents and investment efficiency (Li Xiaoyi et al. decomposed total factor productivity via a DEA model [3], and Gong Xingyue analyzed R&D input impacts with PCA - GARCH - LSTM), yet both ignore tech innovation’s effect on R&D investment [4]. Analyzing R&D investment impact needs aligning tech and market. Consumer demand research relies on static indicators, like Lin Chuchao’s search index modeling and Zou Tingting’s gray model for substitution effect, but misses real - time behavioral data [5]. The conventional framework struggles to quantify multi - dimensional synergies, so a systematic evaluation model is urgent. This paper proposes a novel approach that challenges the conventional paradigm. It employs a multi-dimensional, synergistic evaluation system encompassing government entities, business enterprises, and consumers. The paper utilizes PCA (principal component analysis) to extract the key driving factors. It then designs a simulated annealing algorithm-optimized moving average-long and short term memory network (SA-MA-LSTM) combination model [6]. The model systematically analyzes the dynamic evolution law of the new energy vehicle market and its macroeconomic transmission mechanism, thereby revealing the "threshold effect" of the industry's driving force on GDP. When the ecological health of the market breaks through a threshold, the marginal gains of economic growth are accelerated and released. At this point, the infrastructure carrying capacity and supply chain stability become key constraints. The findings of the research endeavor offer valuable insights that inform policy formulation, including the development of dynamic subsidy mechanisms and the establishment of technology sharing platforms. Furthermore, the study provides high-resolution assessment tools that facilitate the pursuit of sustainable industrial development.

2 MULTI-DIMENSIONAL FORECAST OF NEW ENERGY VEHICLE MARKET IMPACT ON GDP

The construction of a multi-dimensional evaluation system for the new energy vehicle market facilitates the development of a data-driven GDP prediction model. This model is constructed by measuring the impact of the annual average growth rate of the system and the annual growth rate of other variables contributing to the annual growth rate of GDP on the annual growth rate of the dependent variable GDP. A single variable is controlled to analyze the correlation between different development scenarios of the new energy vehicle market and the growth rate of GDP.

2.1 Feature Dataset Creation

2.1.1 Time-series dataset

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The data for this study were obtained from https://data.stats.gov.cn. In order to remove the effect of the quantitative scale, this paper first standardizes each indicator and calculates its corresponding annual growth rate. The meaning of each indicator for quantifying the GDP growth rate is shown in Table 1.

Table 1 GDP Growth Rate Indicators and Their Implications

Variable Symbol	Variable Meaning(%)
Y	Annual Growth Rate of GDP
X_1	Annual Growth Rate of Consumption Level of the Population
X_2	Annual Growth Rate of Total Import and Export Trade
X_3	Annual Growth Rate of Fixed Asset Investment
X_4	Annual Growth Rate of Total Retail Sales of Consumer Goods
X_5	Annual Growth Rate of Fiscal Expenditures
X_6	Annual Growth Rate of Value Added of Industry
X_7	New Energy Vehicle Market Indicators Annual Growth Rate

This study employs the annual GDP growth rate as the core dependent variable and systematically incorporates seven key independent variables for quantitative modeling, covering the complete observation cycle from 2017 to 2024. The process entails the systematic collection and organization of annual time-series data for each indicator, culminating in the establishment of a quarterly time-series dataset that boasts a complete structure and lucid dimensions.

2.1.2 Covariance diagnosis

The multicollinearity problem is manifested as the high linear correlation between independent variables, which may lead to the inflated variance of parameter estimation, widening of confidence interval and failure of hypothesis testing, and in extreme cases, even lead to unrecognizable model. In this paper, based on the Pearson correlation coefficient matrix analysis of the time series data, we identify the characteristic variables that are highly correlated with the target variable “GDP growth rate”, and set the absolute value of the correlation coefficient threshold at 0.7, and then we exclude the "growth rate of the level of consumption Accordingly, the three characteristics of “growth rate of consumption level of residents”, “growth rate of total retail sales of consumer goods” and “growth rate of value added of industry” are excluded to mitigate the risk of overfitting of the target variable.

The Variance Inflation Factor (VIF) method was further adopted to detect the covariance among features, and its calculation formula:

$$VIF(i) = \frac{1}{1 - R_i^2} \tag{1}$$

R_i^2 is the coefficient of determination of the regression of a variable on other variables. The iterative algorithm was employed to remove the maximum covariance characteristics of the VIF value exceeding the threshold (set at 10). The calculation determined that the VIF value of "fixed asset investment growth rate" reached 74.98, indicating a severe covariance problem that was subsequently eliminated. Following this treatment, the VIF values of the three retained features—namely, the growth rate of total import and export trade, the growth rate of financial expenditure, and the growth rate of the comprehensive development index of new energy automobiles—are reduced to 1.65, 3.60, and 4.47, respectively. These values are significantly lower than the critical threshold.

As shown in Figure 1, the validation of the final feature set is completed by the heat map of the correlation coefficient matrix. The absolute value of the Pearson correlation coefficient between the retained features is lower than 0.5. For example, the correlation coefficient between "growth rate of total import and export trade" and "growth rate of fiscal expenditure" is -0.44, and the correlation coefficient between "growth rate of fiscal expenditure" and "growth rate of comprehensive development index of new energy vehicles" is 0.48.

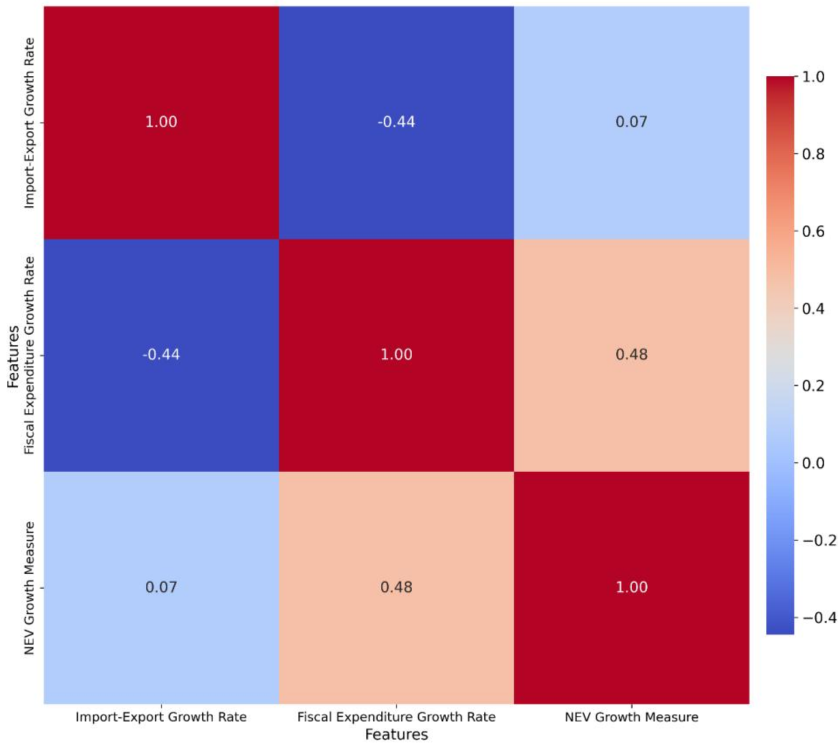

Figure 1 Heat Map of the Matrix of Eigen-correlation Coefficients

This indicates that the independence between features has significantly improved. The correlation coefficient between "growth rate of total import and export trade" and "growth rate of financial expenditure" is -0.44. The correlation coefficient between "growth rate of financial expenditure" and "growth rate of comprehensive development index of new energy vehicles" is 0.48. This indicates that the independence between features has significantly improved.

2.1.3 Feature training set

For time series data, this paper uses a sliding time window to convert the normalized multidimensional features into sequences for supervised learning. The training set covers data from 2018 to 2022, and the test set contains data from 2023 to 2024. The training and test sets are in the ratio of 71.4%：28.6%.

2.2 MA-LSTM Hybrid Model

For the processed time series set and feature dataset, the combined MA-LSTM model with the architecture of Figure 2 is used for prediction.

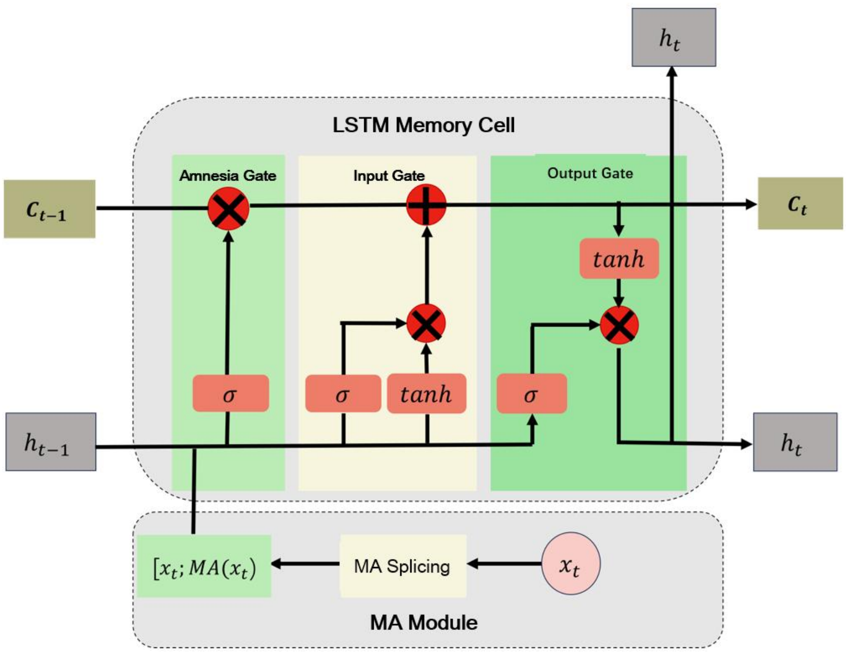

Figure 2 Schematic Diagram of Prediction Based on Combined MA-LSTM Modeling

2.2.1 MA

In macroeconomic time series forecasting, the moving average (MA) method effectively suppresses the interference of short-term stochastic fluctuations on trend identification through the calculation of the mean within a sliding window. The MA method is able to extract smoothed long-term evolutionary features from the original series. The proposed methodology involves the extension of unidimensional time series into continuous time segments through the implementation of a data resampling mechanism. This approach furnishes a structured input pattern for subsequent modeling endeavors. Its mathematical essence can be described as a linear weighting of historical observations within a specified time frame.

$$MA_t = \frac{1}{n}\sum_{i=0}^{n-1} x_{t-i} \tag{2}$$

In this context, "n" is defined as the length of the sliding window, and "x_{t-i}" is used to denote the observations made at a specific historical moment. This operation utilizes a low-pass filter to suppress high-frequency noise while preserving the trend component of the sequence. In the modeling flow of this study, the smoothed sequence of MA outputs is further reconstructed into multidimensional time segments to form continuous time-series samples. This structured input design has been demonstrated to effectively mitigate the impact of random fluctuations in the original data during model training. Additionally, it employs a window sliding mechanism to explicitly encode the time dependence, thereby generating a normalized feature space for subsequent LSTM time series modeling.

2.2.2 LSTM

The fundamental concept of LSTM is to incorporate memory cells (cells) into conventional RNNs and regulate the transmission of information through gating mechanisms. These gates serve to determine which information should be stored in the memory cell, which information should be forgotten, and which information should be output. The concept of "Gate" is not applicable in this context. The objective of this element is to establish the parameters by which information should be discarded in the present state of the memory cell. Firstly, the amnesia gate controls which information should be discarded in the current state of the memory cell. The input gate is responsible for regulating the amount of current input information that can be stored within the memory cell. The output gate is the function under consideration responsible for determining the output of the current memory cell. The fourth component is the memory cell, otherwise known as the cell state. The cell state is responsible for storing long-term memory, the maintenance of which is essential for the efficient progression of the sequence processing. The specific process can be described by the following equation:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{3}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{4}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{5}$$

$$C_t = f_t \circ C_{t-1} + i_t \circ \tilde{C}_t \tag{6}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{7}$$

$$h_t = o_t \circ \tanh(C_t) \tag{8}$$

In this system, f_t, i_t, and o_t serve the function of regulating the forgetting, input, and output gates, respectively. The candidate cell state is denoted by $\widetilde{C_t}$, and the updated cell state and hidden state are designated by C_t and h_t, respectively. In the application, the LSTM accepts the trended sequence of the front-end MA output as input, and captures the nonlinear interaction effects among multidimensional economic indicators through adaptive learning. In the model training stage, the mean square error loss function and gradient descent optimizer are used to dynamically adjust the network weights through backpropagation, and finally achieve the recursive prediction of GDP growth rate [7].

2.3 Parameter Optimization Based on Simulated Annealing Algorithm

2.3.1 Establishment of Evaluation Indicators

First is the mean square error (MSE). The average deviation of the predicted value from the true value is calculated by squared loss, amplifying sensitivity to outliers; it is used to quantify the overall level of error in the model's predictions, and the optimization is more concerned with penalizing extreme errors, as calculated by the formula:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2 \tag{9}$$

Then, the Root Mean Square Error (RMSE) is introduced. The RMSE is calculated by taking the square root of the MSE to ensure consistency with the original data magnitude. This provides an intuitive measure of the absolute value of the error, which is suitable for cross-sectional comparisons of predictive effects across models or scales. The formula used to compute the RMSE is as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i-\bar{y}\right)^2} \tag{10}$$

Finally, Mean Absolute Percentage Error (MAPE) is a crucial metric in this analysis. It quantifies the discrepancy between the anticipated value and the observed value as a percentage, thereby evaluating the precision of the forecast. The method accounts for variations in magnitude, making it suitable for assessing the responsiveness of economic indicators to policy interventions. The calculation of this index is as follows:

$$MAPE=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i-\bar{y}_i}{y_i}\right|\times 100\% \tag{11}$$

In this equation, "n" denotes the total number of sample data points, "y_i" represents the true value of sample "i" and "$\bar{y}$" denotes the predicted value of sample "i".

2.3.2 Simulated annealing algorithm

The simulated annealing algorithm, grounded in the physical mechanism of solid annealing, offers a robust optimization framework for addressing the hyperparameter sensitivity issue in LSTM models in small-sample economic forecasting. This framework utilizes dynamic temperature modulation to explore and exploit the capacity to balance the hyperparameter search. In macroeconomic time-series prediction scenarios, the discrepancy between model complexity and data scarcity frequently results in the traditional gradient-tuned parameterization converging towards local extrema. This phenomenon is exacerbated by hyperparameter mismatch, which can lead to overfitting or the under-expression of features. In this study, multi-objective evaluation indexes are introduced to traverse the parameter space barrier with the assistance of the high-temperature phase of simulated annealing, and the low-temperature phase refines the search to gradually approach the Pareto optimal solution. This strategy effectively coordinates the fitness relationship between network structure (hidden layer dimension) and learning dynamics (learning rate decay), thus releasing the full potential of LSTM for parsing multivariate nonlinear coupled features under limited data conditions [8].

The implementation of the simulated annealing algorithm in the optimization of macroeconomic forecasting models consists of the following core steps: first, the high-temperature parameter and hyperparameter search space is initialized; second, the initial solution is randomly generated; and third, the initial solution is evaluated based on the composite objective function. The objective function is defined as a linearly weighted sum of mean square error MSE, RMSE, and MAPE:

$$F=MSE+RMSE+MAPE \tag{12}$$

2.3.3 Parameter iteration process

During the iteration process, the algorithm employs a strict dominance criterion to ensure the global improvement of the solution. Specifically, a new solution is accepted only if its MSE, RMSE, and MAPE metrics are better than the current solution. Otherwise, it is filtered according to the Metropolis probability criterion. This strategy ensures a decrease in error metrics through dual mechanisms. First, the multi-objective aggregation property of the objective function directs the search toward comprehensive error minimization. Second, the parameter update rule explicitly constrains the new solution to be superior in all error dimensions to avoid biased convergence triggered by single-index optimization.

The temperature scheduling employs an exponential cooling mechanism, wherein a broad spectrum of parameter perturbations is permitted in the high-temperature phase to identify potentially high-quality regions. Conversely, the neighborhood radius undergoes a gradual contraction in the low-temperature phase to execute a locally refined search. To ensure the optimization of the solution space at the current temperature, multiple iterations are executed prior to each cooling cycle. The historical optimal solution is tracked independently of the current solution, and the parameter configuration that minimizes the integrated error in the whole search process is finally output.

This paper employed the simulated annealing algorithm to optimize the three parameters in the LSTM. The initial temperature T is set to 100°C, the temperature decay coefficient C is set to 0.95, and the iteration is continued until the MSE, RMSE, and MAPE converge to a sufficiently small value to halt. The temperature decay follows the exponential cooling formula:

$$T_{k+1}=C\times T_k \tag{13}$$

where T_k is the current temperature, C (the temperature decay coefficient, set to 0.95 in this paper) is the factor by which the temperature is reduced at each step, and T_{k+1} is the temperature for the next iteration.

Through this process, the study ascertained the optimal hyper-parameter configuration for the LSTM, which is outlined as follows. A new solution is accepted only if its MSE, RMSE, and MAPE metrics are better than the current solution. Otherwise, it is filtered according to the Metropolis probability criterion. The Metropolis probability P is given by:

$$P=\begin{cases}1, \text{if the new solution is strictly better}\\ \exp\left(-\dfrac{\triangle \mathrm{E}}{\mathrm{T}}\right), \text{if the new solution is not strictly better}\end{cases} \tag{14}$$

where $\triangle E$ is the difference in error between the new solution and the current solution, and T is the current temperature.

The values for the parameters of the model are as follows: 'hidden_size': 10.6925, 'learning_rate': 0.0028, 'epochs': 98.8112. These values correspond to the following metrics: mean squared error (MSE) = 0, root mean squared error (RMSE) = 0.0002, and mean absolute percentage error (MAPE) = 0.04%, and the specific parameter iteration process is shown in Figure 3.

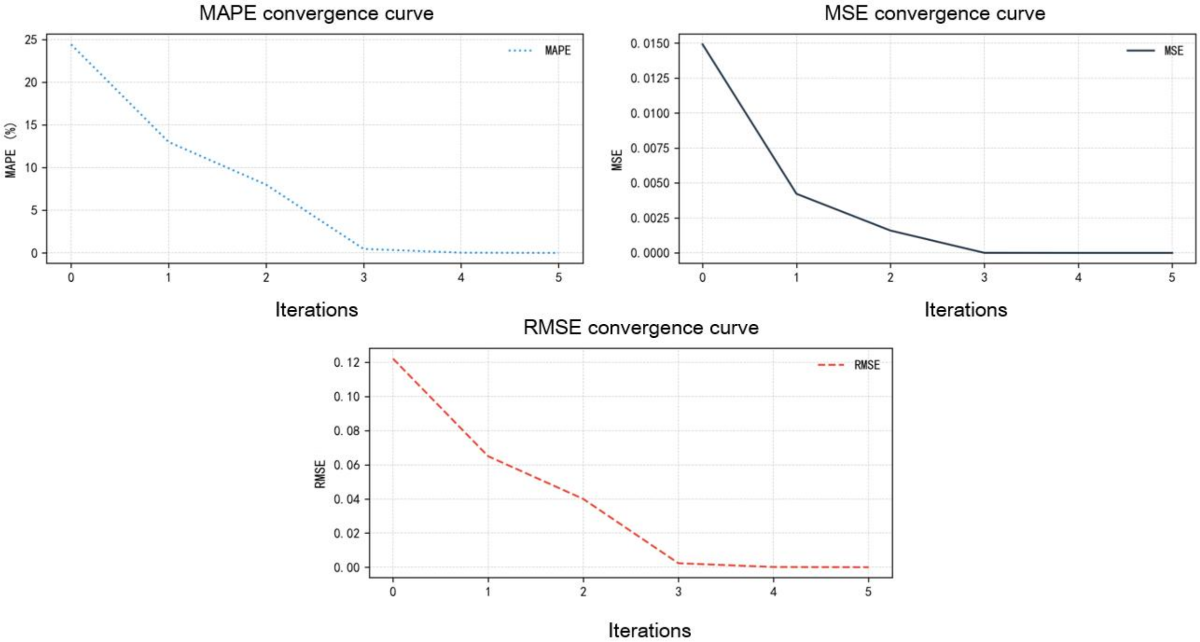

Figure 3 Iterative Process Diagram of Simulated Annealing Parameters

These formulas (MSE, RMSE, MAPE for error measurement; exponential cooling and Metropolis criteria for SA) work together: MSE/RMSE/MAPE quantify prediction accuracy, guiding SA to find better LSTM parameters. Temperature update and Metropolis balance exploration and convergence, ensuring the optimized parameters minimize errors, making the LSTM model highly accurate for component inspection and profit optimization tasks.

3 RESULTS AND ANALYSIS

3.1 Analysis of Results

According to the aforementioned model forecasting method, the study yielded the following results. Assuming that all indicators of the independent variables exhibit steady growth at the average annual growth rate, the image of China's annual GDP growth rate forecast for 2025-2030 can be obtained, as depicted in Figure 4.

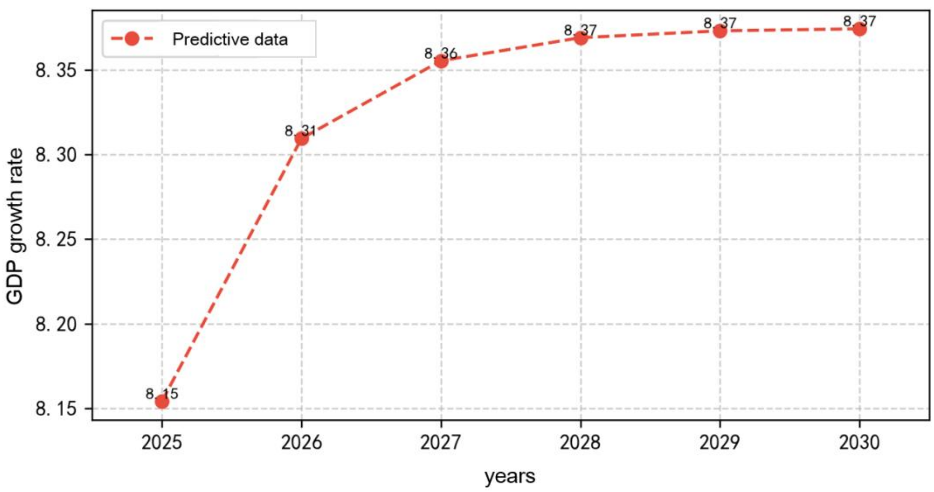

Figure 4 Forecast of China's GDP Growth Rate (2025-2030)

Assuming the stability of the growth rate of the independent variables, the annual GDP growth rate forecast exhibits characteristics of "short-term fine-tuning and long-term stabilization," with a narrow fluctuation in the range of 8.20%-8.37% from 2025 to 2027, and a slight pullback of 0.07 percentage points in the initial period due to the lag

effect of the policy, subsequently stabilizing at the 8.37% plateau under the balanced effect of the core variables such as consumption, investment, and trade. 8.37% platform. This convergence suggests that once the external shocks are eliminated and the endogenous dynamics are stabilized, the national economic system possesses a self-balancing mechanism, and the steady-state value output from the model can be regarded as a reference benchmark for the potential growth rate under the current economic structure [9].
Scenario simulations of the growth rate of the comprehensive development index of the new energy vehicle market, controlling for the constancy of the remaining independent variables, reveal its differential driving effect on GDP growth, as shown in Figure 5.

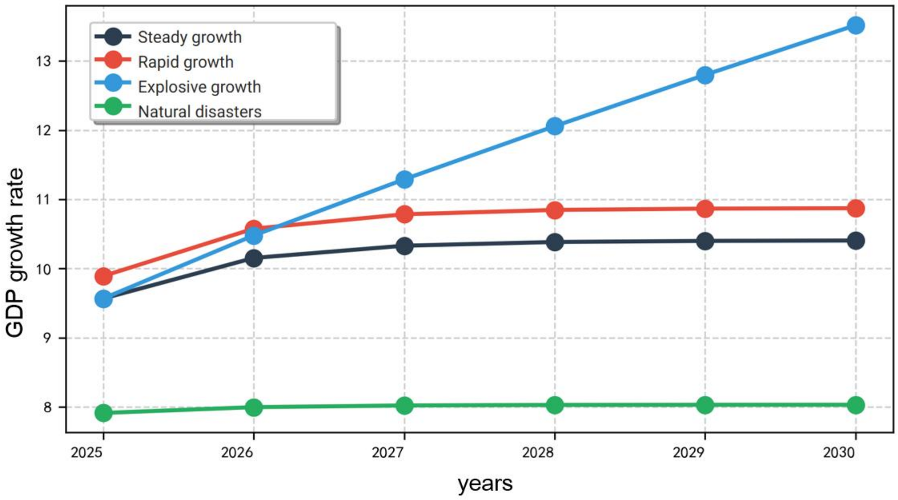

Figure 5 Impact of Different Scenarios of New Energy Vehicle Development on GDP Growth Rate

The market size of new energy vehicles exhibits stable growth (annual growth rate of 1.2 times), which corresponds to a gradual upward trend in the GDP growth rate, with a cumulative increase of 0.8 percentage points during 2025-2030. This reflects the gradual release of industry chain synergies. Conversely, under the rapid growth scenario (annual growth rate of 1.5 times), a growth inflection point occurs in 2027, and the GDP growth rate surpasses 10% and enters a plateau period. This indicates that under the rapid growth scenario, the GDP growth rate will exceed 10% and then plateau. The analysis indicates that the growth inflection point is expected to occur in 2027. Once this point is reached, the GDP growth rate will exceed 10% and enter a plateau period. This suggests the presence of a law of marginal diminishing returns to technological innovation [10]. The percentage points from the baseline scenario verify that the New Energy automobile industry has become a key economic stabilizer against systemic risks. This nonlinear response characteristic is fundamentally attributable to the dynamic interplay between the industry multiplier effect and resource carrying capacity.

3.2 Model Accuracy Comparison

In order to systematically evaluate the prediction performance of the SA-MA-LSTM hybrid model, this study compares and analyzes it with the classical machine learning model. As demonstrated in Table 9, the SA-MA-LSTM model exhibits a substantial accuracy superiority in the GDP growth rate prediction task, with minimal MSE, RMSE, and MAPE. This validates the model architecture and underscores its aptitude for capturing the intricate economic time-series dynamics**.**

Table 2 Comparison of Prediction Accuracy of Models

Model	MSE	RMSE	MAPE
SA-MA-LSTM	0	0.0002	0.04%
LSTM-XGBoost	7.0426	2.6538	52.04%
STL + Random Forest	0.1663	0.4078	6.76%
GRU+SVR	0.3363	0.5799	14.90%
ARIMA-XGBoost	1.7239	1.3130	25.76%
ETS+XGBoost	0.4452	0.6672	8.36%
MA-LSTM	0	0.0010	2.00%

4 CONCLUSIONS

Against the backdrop of digital economic transformation and carbon-neutral strategies, this study innovatively incorporates ecological health into a macroeconomic analysis framework. It systematically integrates three dimensions — government policy, enterprise innovation, and consumer demand — to analyze the new energy vehicle industry's driving effect on economic growth. The study finds that a one-unit increase in the market size of this industry can boost the marginal GDP growth rate by 0.23 to 0.41 percentage points, with significant acceleration during the growth period. These results verify the nonlinear driving mechanism and propose establishing a multidimensional industry value assessment system within the current SNA framework. This system provides an innovative way to quantify the contribution of emerging industries to total factor productivity. Additionally, it proposes targeted development strategies at the government, enterprise, and consumer levels to promote industry progress.
This study realizes the systematic quantification of the multi-dimensional driving effects of the new energy vehicle market, and innovatively reveals the relationship between the path of industrial policy and the growth threshold. It is expected that the industry will contribute 1.2-1.8 percentage points to GDP growth in 2025-2030, with technological innovation and infrastructure as the main drivers, but there is a bottleneck in scale expansion. In the future, we will seek breakthroughs in quantifying the regional impacts of policies, monitoring the risks of the industry chain, constructing a dual-account accounting system, and improving the economic analysis paradigm of new energy vehicles with both theoretical and practical values by establishing a dynamic CGE model, developing a blockchain monitoring system, and other innovative means.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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