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Grey Bass Model Based on Weakening Buffer Operator and its Application in New Energy Vehicle Sales Forecast

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Abstract

With the enhancement of global environmental awareness and the promotion of technological innovation, the new energy vehicle market has shown a rapid growth trend. However, due to the complexity and variability of the new energy vehicle market, accurately forecasting its sales has become a challenge. In this paper, a grey Bass model based on the weakening buffer operator is proposed for the prediction of NEV sales. This model combines the advantages of the grey system theory and Bass diffusion model, and preprocesses the data through the weakening buffer operator, which improves the accuracy of the prediction. This paper first introduces the basic principle of the grey system theory and Bass diffusion model, then elaborates the construction method of the grey Bass model based on the weakening buffer operator, and verifies the effectiveness of the model through an example. The research results show that the model can better predict the sales volume of new energy vehicles, and provide a scientific basis for the decision of related enterprises.

Keywords: grey bass model, new energy vehicle, sales volume forecast, buffering operator

1. Introduction

As an emerging force in the automobile industry, new energy vehicles are developing rapidly around the world. The government's supportive policies, consumers' emphasis on environmental protection and the continuous advancement of technology have combined to boost the sales growth of new energy vehicles. However, due to the uncertainty of market demand, the unpredictability of technological development and the impact of policy changes, it has become a difficult problem to accurately forecast the sales volume of NEVs. Grey system theory is an effective way to deal with uncertainty problems, which uses known information to explore and predict unknown information. Bass diffusion model is a commonly used market diffusion model, which can describe the diffusion process of new products in the market. This paper combines the grey system theory and Bass diffusion model, and proposes a grey Bass model based on the weakening buffer operator, which is used to forecast the sales volume of new energy vehicles.

1.1 Overview of Bass Diffusion Model

The Bass diffusion model is a model that describes the diffusion process of a new product in the market. The model was proposed by Frank Bass in 1969 to predict the market diffusion of consumer durables. According to the Bass diffusion model, the diffusion process of new products is mainly affected by two factors: innovators and imitators. Innovators refer to those consumers who are willing to try new products and are not influenced by other consumers. And imitators are consumers who are influenced by other consumers to buy new products. Based on Bass model, the literature(Ma and Zhang, 2018) studies the diffusion mode of China's new energy vehicles and effectively analyzes the trend of China's new energy vehicle market. Many scholars have studied the optimization of Bass model. Liang et al.(Liang, 2021) proposed a new parameter estimation method (OPE) of Bass model in the framework of system dynamics theory. Literature(Jukic, 2011) considers the nonlinear weighted least squares fitting method (TLS) to estimate Bass model parameters. For the model itself, Gao et al.(Gao et al., 2021) proposed a spatiotemporal heterogeneous Bass model and a featue-driven heterogeneous Bass model to predict the popularity of individual tweets in the early and stable stages.

1.2 Overview of Grey System Theory

Since the establishment of grey system theory by Professor Deng Julong in 1982, grey model has formed a huge research system. In order to improve the accuracy of the grey model, some scholars add the dependent variable lag term, linear correction term and random disturbance term to the traditional GM(1,N) model, and put forward a new multi-variable grey prediction model(Zeng et al., 2019). Zeng et al.(Zeng et al., 2020) used a new structure grey Verhulst model to predict China's tight natural gas production and achieved good forecasting results. Yan et al.(Yan et al., 2022) proposed a grey model derived from fractional Hausdorff to improve the prediction accuracy of the traditional grey model. Tu et al.(Tu and Chen, 2021) proposed unequal accumulation method to reduce the loss of difference information of grey model.

Due to the good prediction effect of grey model on small sample data, some scholars try to combine grey model with other models and theories for prediction, such as Bernoulli model(Ding et al., 2021), Z-number theory[11], Tucker tensor decomposition(Duan et al., 2020), Logistic model(Duan and Pang, 2023) and so on. Duan et al. (Duan and Liu, 2021; Duan et al., 2022)built a grey model based on the differential equation model of economic system to analyze the dynamic change process of energy prices, which can effectively describe the dynamic change law of energy price system. The literature(Duan and Wang, 2023) organically combines the modulation mechanism of partial differential with the grey prediction model, and uses the partial derivative of the mean sequence to establish a partial grey prediction model with control matrix.

However, due to the central and local dual subsidy policies in 2014, China's new energy vehicle sales soared at a high growth rate. Since then, due to the introduction and changes of various policies, their growth rate has shown great fluctuations. These external policy impacts on the new energy vehicle system lead to the growth rate of new energy vehicle sales is extremely unstable, and the traditional time series model may be difficult to accurately predict its future development trend. Therefore, He et al.(He et al., 2020) and Ding et al.(Ding et al., 2021) introduced buffer operators into the grey model to predict the sales of new energy vehicles. Buffering operator is a new concept proposed by Professor Liu Sifeng for modeling and analysis of such impact disturbance systems. When the system is hit by impact and its growth rate increases sharply, a weakening buffering operator can be applied to it to reduce the random disturbance hidden in the original sample. According to the characteristics of the new energy vehicle system, it is an effective measure to model the original data after preprocessing the action of the weakening buffer operator.

In this paper, based on the above research, combined with the idea of grey modeling, the Bass model and the grey model are sorted to get the grey Bass model. At the same time, taking into account the interference of external factors, the buffer operator is introduced. Through the example data, it is proved that the constructed grey Bass model (WBO-GBM(1,1) model) combined with the weakening buffer operator has higher simulation accuracy in the fitting of emerging industry data than the traditional Bass model and the grey model. Finally, the annual sales volume of China's new energy vehicles in the next three years is forecasted, aiming to provide certain decision-making reference for the planning of the new energy vehicle industry.

2. WBO-GBM(1,1) Model Construction

2.1 Establishment of Bass Model

The basic assumption of Bass model is that potential users' adoption of a certain product is triggered by two behaviors, namely innovation and imitation. People accept new products and services through innovation or imitation, and the adoption of these new products and services is triggered by different stimuli. Potential users are divided into early adopters and imitators, the former being easily stimulated by external stimuli when accepting new products and daring to use new technologies; The latter are susceptible to the internal influence of people who are already using the new product in their social environment. Based on the above assumptions, the Bass model can be defined as follows.

Definition 1: Assuming that the $x(t)$ is the number of people using the new technology at any time, the Bass model can be expressed in the following form:

$$\frac{dx(t)}{dt} = p\left(m - x(t)\right) + q\frac{x(t)}{m}\left(m - x(t)\right), t \geq 0, p, q > 0 \tag{1}$$

Where, m is the maximum market potential, that is, the maximum adoption that can be realized in the diffusion process; p is the innovator coefficient, q is the corresponding imitator coefficient, and the larger the value, the faster the technology spread; $dx(t)/dt$ represents the adoption rate, which is proportional to the remaining market $\left(m - x(t)\right)$.

Bass model expresses the essence of new product diffusion process with mathematical formula, and simulates the process of new product acceptance by users through a simple differential equation, which greatly simplifies people's understanding of innovation diffusion and systematizes it.

2.2 Weakening Buffer Operator Based on New Information

Due to the impact of various external factors, the historical time series of the system always deviates from the established path, which leads to the nonlinear and non-smooth sequence. Compared with the original sequence with more randomness and perturbation terms, the sequence processed by buffering operator is smoother and is usually more accurate for modeling. In this subsection, we will introduce a new information-based attenuated buffering operator that takes into account all the new and old information in the original sequence, and gives more weight to the new information.

Definition 2: It is $X_0^{(0)} = \left(x_0^{(0)}(1), x_0^{(0)}(2), x_0^{(0)}(3), \cdots, x_0^{(0)}(n)\right)$ assumed to be a sequence of system behavior characteristics, and the original sequence has some random perturbations, which makes it difficult to mine its internal development law. make

$$X^{(1)} = X_0^{(0)}D = \left(x_0^{(0)}(1)d, x_0^{(0)}(2)d, x_0^{(0)}(3)d, \cdots, x_0^{(0)}(n)d\right) = \left(x^{(1)}(1), x^{(1)}(2), x^{(1)}(3), \cdots, x^{(1)}(n)\right) \quad (2)$$

Of which,

$$\begin{aligned} x_0^{(0)}(k)d &= \frac{2}{(n+k)(n-k+1)}\left[kx^{(0)}(k) + (k+1)x^{(0)}(k+1) + \cdots + nx^{(0)}(n)\right] \\ &= \frac{2}{(n+k)(n-k+1)}\sum_{i=k}^{n} ix^{(0)}(i) \end{aligned} \quad (3)$$

In the above formula, d is the buffering operator, that is, to weaken the buffering sequence.

2.3 GBM(1,1) Model Construction and Solution

2.3.1 Model Construction

Definition 3: Set Bass model as shown in definition 1, sequence $X^{(0)}$ and $X^{(1)}$ as shown in definition 2, and arrange formula (1) according to grey modeling mechanism

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b\left[x^{(1)}(t)\right]^2 + c \quad (4)$$

Where $a = p - q, b = -\frac{q}{m}, c = pm$

Definition 4 : Infrared formula can be obtained by integrating both sides of formula (4) over $[k-1, k]$

$$x^{(1)}(k) - x^{(1)}(k-1) + a\int_{k-1}^{k} x^{(1)}(t)dt = b\int_{k-1}^{k}\left[x^{(1)}(t)\right]^2 dt + c \quad (5)$$

In order to simplify the calculation, we make the following approximation:

$$\begin{aligned} &\int_{k-1}^{k} x^{(1)}(t)dt = rx^{(1)}(k) + (1-r)x^{(1)}(k-1) = z^{(1)}(k) \\ &\int_{k-1}^{k}\left[x^{(1)}(t)\right]^2 dt = r_1\left[x^{(1)}(k)\right]^2 + (1-r_1)\left[x^{(1)}(k-1)\right]^2 = z_1^{(1)}(k) \end{aligned}$$

And there is $x^{(1)}(k) - x^{(1)}(k-1) = x^{(0)}(k)$, therefore, formula (5) can be expressed as

$$x^{(0)}(k) + az^{(1)}(k) = bz_1^{(1)}(k) + c \quad (6)$$

Formula (6) is called the grey Bass model, denoted as GBM(1,1) model, and $z^{(1)}(k)$, $z_1^{(1)}(k)$ called the background value.

2.3.2 Parameter estimation

Theorem 1: For a given sequence, the parameter estimates of the GBM(1,1) model are

$$P = \left(\hat{a}, \hat{b}, \hat{b}_2, \hat{c}\right)^T = \left(B^T B\right)^{-1} B^T Y \quad (7)$$

where

$$B=\begin{pmatrix}-z^{(1)}(2) & z_1^{(1)}(2) & 1\\ -z^{(1)}(3) & z_1^{(1)}(3) & 1\\ \vdots & \vdots & \vdots\\ -z^{(1)}(n) & z_1^{(1)}(n) & 1\end{pmatrix}, Y=\begin{pmatrix}x^{(0)}(2)\\ x^{(0)}(3)\\ \vdots\\ x^{(0)}(n)\end{pmatrix} \tag{8}$$

Proof:

If the error sequence is $\varepsilon = Y - BP$, sum of error squares is $S=\|Y-BP\|_2^2=(Y-BP)^T(Y-BP)$, then

$$\begin{aligned}\frac{\partial S}{\partial P}&=\frac{\partial\left[(Y-BP)^T(Y-BP)\right]}{\partial P}\\ &=(Y-BP)^T(-B)+(-B)(Y-BP)\\ &=-2B^TY+2B^TBP\end{aligned} \tag{9}$$

$$\frac{\partial^2 S}{\partial P^2}=2B^TB \tag{10}$$

It is known from the expression of the Hesse matrix that $\frac{\partial^2 S}{\partial P^2}$ is a positive definite matrix, so at $\frac{\partial S}{\partial P}=0$, the error matrix S takes the minimum value, so it can be obtained

$$-2B^TY+2B^TBP=0\Rightarrow P=\left(B^TB\right)^{-1}B^TY \tag{11}$$

2.3.3 Time Response Solution

Theorem 2: The time response formula of GBM(1,1) model is

$$x^{(1)}(k)=\begin{cases}x^{(1)}(1), k=1\\ \dfrac{-B\pm\sqrt{\Delta}}{2A}, \Delta>0\\ \dfrac{-B}{2A}, \Delta=0\\ \dfrac{-B\pm\sqrt{-\Delta}i}{2A}, \Delta<0\end{cases} \tag{12}$$

Where,

$$\begin{cases}A=br_1\\ B=-(1+ar)\\ C=\left[1-a(1-r)\right]x^{(1)}(k-1)+b(1-r_1)\left[x^{(1)}(k-1)\right]^2+c\\ \Delta=B^2-4AC\end{cases}$$

Proof:

Plugging the $\begin{cases}z^{(1)}(k)=rx^{(1)}(k)+(1-r)x^{(1)}(k-1)\\ z_1^{(1)}(k)=r_1\left[x^{(1)}(k)\right]^2+(1-r_1)\left[x^{(1)}(k-1)\right]^2\end{cases}$ into (6) we can get

$$x^{(1)}(k)-x^{(1)}(k-1)+a\left[rx^{(1)}(k)+(1-r)x^{(1)}(k-1)\right]=b\left[r_1\left[x^{(1)}(k)\right]^2+(1-r_1)\left[x^{(1)}(k-1)\right]^2\right]+c \tag{13}$$

Then tidy it up

$$br_1\left[x^{(1)}(k)\right]^2-(1+ar)x^{(1)}(k)+\left[1-a(1-r)\right]x^{(1)}(k-1)+b(1-r_1)\left[x^{(1)}(k-1)\right]^2+c=0 \tag{14}$$

Define that $\begin{cases} A = br_1 \\ B = -(1+ar) \\ C = \left[1-a(1-r)\right]x^{(1)}(k-1)+b(1-r_1)\left[x^{(1)}(k-1)\right]^2+c \end{cases}$, then formula (14) can be reduced to

$$A\left[x^{(1)}(k)\right]^2 + Bx^{(1)}(k) + C = 0 \tag{15}$$

The solution of the quadratic equation with one variable is

$$\hat{x}^{(1)}(k) = \begin{cases} x^{(1)}(1), k=1 \\ \dfrac{-B \pm \sqrt{\Delta}}{2A}, \Delta > 0 \\ \dfrac{-B}{2A}, \Delta = 0 \\ \dfrac{-B \pm \sqrt{-\Delta} i}{2A}, \Delta < 0 \end{cases} \tag{16}$$

2.4 Indicators to Evaluate the Validity of the Model

Model error is an important index to evaluate the reliability and practicability of the model. To evaluate the validity of the model, this paper uses absolute percentage error (APE) and mean absolute percentage error (MAPE) to test the overall performance of the model, and the formula is defined as follows:

$$APE = \left|\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right| \times 100\% \tag{17}$$

$$MAPE = \frac{1}{(n-1)}\left(\sum_{k=2}^{n}\left|\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)}\right|\right) \times 100\% \tag{18}$$

3. China's New Energy Vehicle Sales Simulation

At present, a new round of scientific and technological revolution and industrial transformation is booming, and the technology integration of automobiles and energy, transportation, information and communication is accelerating, and electrification, intelligence, and networking have become the development trend and trend of the automobile industry. Profound changes are taking place in the form of automobile products, transportation modes and energy consumption structure, providing unprecedented development opportunities for the new energy automobile industry. It is foreseeable that new energy vehicles will become the main direction of the transformation and development of the global automobile industry and an important engine to promote the sustained growth of the world economy. The forecast of the future sales volume of the new energy automobile industry is conducive to the timely adjustment of relevant policies and guidelines and reasonable planning of industrial development. Therefore, in this section, China's new energy vehicle sales volume is simulated to test the performance of our proposed model.

3.1 Data Collection and Pre-Processing

Thanks to the proposal of various industrial support policies and the advancement of new energy vehicle technologies, the country has benefited from the development of various industrial support policies since 2013, according to data released by the China Association of Automobile Manufacturers (http://www.caam.org.cn) and the China Passenger Car Market Information Association (http://www.cpcaauto.com). The market size of new energy vehicles has grown exponentially. Since 2021, driven by conditions such as the alleviation of the epidemic and the recovery of the national economy, the new energy automobile industry has entered a stage of accelerated growth. According to statistics, the annual sales volume of China's new energy vehicles in 2021 will reach 3.5 million, an increase of more than 100%, and the annual sales volume in 2022 will reach 6.887 million, an increase of 96.77%. Both far exceed the year-on-year growth of 12.6% in 2020, and the sales of other countries have also increased significantly in the past two years. Therefore, the data of 2021 and 2022 can be regarded as the shock and disturbance change points of the system, which need to be processed to a certain extent. The weakening buffering operator described above is used to preprocess the data:

$$\begin{aligned} x_0^{(0)}(k)d &= \frac{2}{(n+k)(n-k+1)}\left[kx^{(0)}(k)+(k+1)x^{(0)}(k+1)+\cdots+nx^{(0)}(n)\right] \\ &= \frac{2}{(n+k)(n-k+1)}\sum_{i=k}^{n} ix^{(0)}(i) \end{aligned} \tag{19}$$

The sales data of China's new energy vehicles from 2013 to 2023 are shown in Table 1.

Table 1. Sales of new energy vehicles in China from 2013 to 2023

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Sales	1.76	5.21	17.84	32.48	54.96	92.26	104.04	136.7	350	688.7	958.7

It is obviously a monotonically increasing sequence. The above data are preprocessed according to equation (19), and the results are shown in Table 2.

Table 2. Sales volume of new energy vehicles in China after pre-processing

Year	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Sales	354.98	360.41	371.69	389.38	414.87	450.16	497.88	570.43	686.09	830.13	958.7

3.2 Verify the WBO-GBM(1,1) Model

In the application part, the sales volume of new energy vehicles in China is mainly selected from 2013 to 2022. The original data and the pre-processed data are shown in Table 2 and Table 3. The pre-processed data is modeled and analyzed, and the data is divided into two groups, in which the data from 2013 to 2021 is used as the simulation data set, and the data from 2022 is used as the forecast data. Particle swarm optimization (PSO) was used to solve the hyperparameters of GBM(1,1) model, and GBM(1,1) model, Bass model, GM(1,1) model, Verhulst model and DGM(1,1) model were respectively used to simulate and predict the pre-processed data. The results are shown in Table 3.

Table 3. Simulation results of China's new energy vehicle sales based on weakening buffer sequence

Year	Original value	GBM(1,1)		Bass		GM(1,1)		Verhulst		DGM(1,1)	
		Simulated value	APE(%)	Simulated value	APE(%)	Simulated value	APE(%)	Simulated value	APE(%)	Simulated value	APE(%)
2013	354.98	354.98	0.00	288.395	18.76	354.98	0.00	354.98	0.00	354.98	0.00
2014	360.41	361.482	0.30	321.179	10.89	301.681	16.30	272.592	24.37	302.958	15.94
2015	371.69	371.044	0.17	357.685	3.77	338.856	8.83	200.895	45.95	340.168	8.48
2016	389.38	387.897	0.38	398.333	2.30	380.611	2.25	257.898	33.77	381.948	1.91
2017	414.87	413.477	0.34	443.591	6.92	427.512	3.05	326.067	21.41	428.86	3.37
2018	450.16	450.138	0.01	493.982	9.73	480.191	6.67	404.401	10.17	481.533	6.97
2019	497.88	501.666	0.76	550.083	10.49	539.363	8.33	489.758	1.63	540.676	8.60
2020	570.43	574.237	0.67	612.541	7.38	605.825	6.21	576.32	1.03	607.084	6.43
2021	686.09	678.324	1.13	682.070	0.59	680.477	0.82	655.675	4.43	681.647	0.65
2022	830.13	832.764	0.32	759.466	8.51	764.329	7.93	717.921	13.52	765.368	7.80
$MAPE_{simu}$(%)		**0.45**		**7.93**		**6.71**		**17.36**		**6.68**	
2023	958.7	950.883	0.82	845.615	11.80	858.513	10.45	753.844	21.37	859.373	10.36
$MAPE_{pre}$(%)		**0.82**		**11.80**		**10.45**		**21.37**		**10.36**	

The results show that the GBM(1,1) model based on the weakening buffer sequence has the lowest errors in both the simulation and prediction parts, while the other models have more than 5% errors in both the simulation and prediction parts. This significant advantage indicates that GBM(1,1) model preprocessed by buffering operators has high accuracy and stability when processing time series data, especially complex data affected by multiple factors such as China's new energy vehicle sales. Therefore, it can be reasonably inferred that the GBM(1,1) model is suitable for China's new energy vehicle sales forecast, and can provide policy makers, automobile manufacturers and market analysts with reliable future trend prediction, and help industry decision-making and strategic planning.

4. China's New Energy Vehicle Sales Forecast

With increasing environmental pollution, the demand for new energy vehicles is growing, and the new energy vehicle industry is expected to develop rapidly in the next three years. The above cases verify the feasibility of WBO-GBM(1,1) model in predicting sales of new energy vehicles. Compared with Bass model, GM(1,1) model, Verhulst model and DGM(1,1) model, the error evaluation indexes of WBO-GBM(1,1) model are all within a reasonable range (<3%). This means that the proposed optimization model has successfully captured the trend characteristics of new energy vehicle sales data. Therefore, we further forecast the development trend of China's new energy vehicles in the next three years, and the results are shown in Table 4.

Table 4. Sales Forecast of new energy vehicles in China in the next three years (unit: 10,000 units)

Year	2024	2025	2026
Sales volume	1001.288	1135.539	1287.790

For now, China's new energy vehicle sales will continue to grow steadily in the next three years, and will exceed 10 million in 2024. But it is worth noting that after surging sales in 2021 and 2022, China's NEV growth rate will gradually slow down. China's projected sales volume in 2024 is 10012,288 million, an increase of 4.44% year-on-year, which is significantly reduced from the growth rate of 156.4% in 2021 and 96.77% in 2022. The growth rate in 2025 and 2026 will also slow down.

5. Result Analysis and Suggestions

The forecast of the sales volume of new energy vehicles is conducive to the timely adjustment of the development strategy of new energy vehicle enterprises, and provides certain reference significance for people's vehicle purchase choice. In this paper, the WBO-GBM(1,1) model is constructed to reasonably forecast the sales volume of new energy vehicles, which has certain reference value for the construction of national power grid and charging facilities by the government. According to the existing data, China's new energy vehicle sales in 2022 has accounted for 25.64% of the total automobile sales, early to reach The State Council "New energy automobile Industry Development Plan (2021-2035)" in 2025 new energy vehicle sales to reach about 20% of the total automobile sales development goal. According to the forecast results of the WBO-GBM(1,1) model, the sales volume of new energy vehicles will continue to grow in the next three years, showing a good trend. However, the growth rate of new energy vehicles is gradually slowing down, which indicates that the development of new energy vehicle sales may be about to stabilize. Based on the above results, we put forward the following suggestions for the development of the new energy automobile industry:

(1) To promote the intelligent development of new energy vehicles, we must practice the new development concept, rely on innovation-driven connotation growth, vigorously improve the independent innovation ability of enterprises, and break through key core technologies as soon as possible;

(2) firmly adhere to the strategic base point of expanding domestic demand, adhere to the people-centered, through intelligent network technology and service platform, improve the vehicle experience and value, so that high-quality new energy vehicles are within reach, truly realize the popularization of high-end products and the intelligence of mass products, so that ordinary consumers share the development results of intelligent science and technology progress;

(3) Further refine the evaluation criteria for new energy vehicle enterprises and even upstream battery suppliers, establish a comprehensive scoring mechanism for safety, durability, charging efficiency, energy density, driving range and other indicators, and introduce relevant policies to extend the three-guarantee period of new energy vehicles to dispel consumers' doubts.

6. Conclusion

Sales prediction of new energy vehicles is a modeling problem of nonlinear data. Based on Bass diffusion model, this paper proposes a grey Bass model using weakening buffer sequence for modeling. On this basis, according to the grey derivative information covering principle, the discrete difference form of the model is given, and the background value is optimized by particle swarm optimization algorithm, and the WBO-GBM(1,1) model is obtained. In order to test the validity of the model, the new WBO-GBM(1,1) model is tested by the sales sequence of new energy vehicles in China from 2013 to 2023, and the following conclusions are obtained:

(1) WBO-GBM(1,1) model can grasp the potential law of system changes from the time series, and effectively reduce the randomness of the data and increase the reliability of parameter estimation through a one-time

accumulation of the original data. In nonlinear data modeling experiments, WBO-GBM model has higher prediction accuracy than the traditional Bass model and grey model.

(2) It is accurate and reasonable to use the WBO-GBM(1,1) model to predict the future sales volume of new energy vehicles. In the case analysis, all evaluation indicators of the WBO-GBM(1,1) model are superior to other models.

(3) The forecast and simulation results show that since 2021, China's new energy automobile industry has ushered in a period of rapid growth, the market competitiveness has been significantly enhanced, and the development goal of 2025 new energy vehicle sales accounting for 20% of the total automobile sales has been reached in 2022 ahead of schedule. According to this development trend, the new energy automobile industry will continue to promote China from an automobile power to an automobile power in accordance with the basic principles of market-led, innovation-driven, coordinated promotion and open development, and promote the improvement of energy conservation and emission reduction level and social operation efficiency.

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