Research Article

An Optimization Grey Bernoulli Model and Its Application in Forecasting Oil Consumption

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Energy consumption in the world is mainly dependent on fossil energy, and oil is one of the main energy sources. Accurate prediction of oil consumption can provide an important basis for national energy security, which can provide reference and early warning for the implementation of the environmental strategy developed by the government. According to the nonlinearity of the energy system, this paper uses the principle of the grey nonlinear prediction model NGBM(1,1) to improve the background value of the model, and by the simulated annealing algorithm, we put forward the optimized grey nonlinear model ONGBM(1,1). At the same time, the model is applied to the oil consumption of China, Chile, Mexico, and Japan. Based on the validity analysis of the existing data of the four countries, the model ONGBM(1,1) is basically superior to the other six grey forecast models. Finally, ONGBM(1,1) is used to predict the oil consumption of the four countries in the next five years, which can provide effective information for energy economic policy.

1. Introduction

With the continuous development of the economy, the increasing consumption of fossil energy has caused high carbon emissions, which has led to a series of environmental and ecological problems. In particular, it is the main cause of global warming, greenhouse effect, and extreme weather. Ecologically sustainable development requires us to pay attention to energy consumption. Energy development is currently in a critical period of transformation and change, facing unprecedented opportunities and challenges. In terms of energy consumption results, nowadays, energy consumption in the world is mainly dependent on fossil energy. Oil is one of the major energy sources, and the proportion of oil in energy consumption shows a rising trend, and oil affects the development of the global economy. Thus, the prediction of oil consumption is a necessary basis for the formulation of economic and social plans and can also provide an important basis for national energy security.

In addition, with the rapid development of the world, the global economic structure has undergone major changes,

and the energy structure has also changed accordingly. Therefore, some historical data may have little reference value for the current energy situation or the future energy development trend. Therefore, only the data of recent years are reliable for energy consumption forecasts. In a modelling system with small samples and little information, the grey prediction model has more advantage, which is suitable for some systems with unclear information, and its forecast is to generate the original data sequence, weaken the randomness of the original data, to mine the hidden laws in the data sequence, and finally simulate and predict the data through the reduction operation.

The grey model was proposed by Deng [1] based on the grey theory of small sample and poor information system. The grey prediction model is one of the core parts of the grey system, which is characterized by a few data modelling and simple modelling. At present, it is widely used in energy [2–5], transportation [6–9], environment [10, 11], and other industries [12–18].

Grey prediction model is also expanded from GM(1,1) model for predicting exponential growth data to univariate

discrete models DGM(1,1) model and NDGM(1,1) model [19, 20], as well as the single variable nonlinear grey Verhulst model and grey Bernoulli NGBM (1,1) model [21, 22]. Since there are many influencing factors in the model, univariate model is extended to multivariate models, such as GM(1,N), NGM(1,N), GMC(1,N), and other multivariate models [23–25]. At the same time, a lot of researchers work on improving the accuracy of the model, such as optimizing the background value of the grey model, using appropriate algorithms to optimize the parameters, and combining with other machine learning methods to improve the accuracy, which promotes the development and improvement of the grey theoretical system.

The grey prediction model has been widely used by domestic and foreign scholars when predicting energy consumption. Ma et al. [26] established a delayed fractional-order grey prediction model to predict coal and natural gas consumption in Chongqing, China, using the grey Wolf optimization algorithm; Jia et al. [27] proposed a modified GM(1,1) model by Markov chain to predict coal consumption in Gansu Province; Wu et al. [28] used the new multivariable grey prediction model to forecast the power consumption in Shandong Province. Wang et al. [29] proposed the combinational optimization model of GM(1,1)-ARIMA based on the IOWGA operator to predict the total coal consumption in the United States. Duan et al. [30] proposed a new model based on the property of data accumulation and fractional-order accumulation and used particle swarm optimization algorithm to seek the optimal fraction and then predicted the crude oil consumption in China from 2015 to 2020 by the model. In addition, the authors in [2–5, 31–33] have effectively predicted various energy consumption methods, and the grey model has achieved good results in the field of energy.

The energy system presents obvious nonlinear characteristics in real life. Based on this characteristic, in this paper, the nonlinear grey Bernoulli NGBM(1,1) prediction model was optimized, and its modelling principle was perfected by optimizing the background value of the model, the model nonlinearity is embodied, the model structure is optimized, and the model accuracy is improved.

The simulated annealing algorithm is combined with the probabilistic jumping to randomly find the global optimal solution of the objective function in the solution space. Compared with other greedy algorithms, which may be trapped in the local optimal solution and cannot find the solution, the simulated annealing algorithm can jump out of the local optimal solution probabilistically and eventually approach the global optimal solution. At present, many scholars of grey systems also apply this algorithm to optimize grey models. For example, Luo et al. [34] put forward a new grey CCRGM(1,1) prediction model by using the simulated annealing algorithm to optimize and apply it to the prediction of clean energy; Pai and Hong [35] proposed a combined method based on support vector machines and the simulated annealing algorithms for annual electricity load forecasting. Guo et al. [36] optimized the grey prediction model based on the simulated annealing algorithm and applied it to landslide prediction. In this paper, the

simulated annealing algorithm is used to calculate the optimal undetermined coefficient in consideration of the operation characteristics, time processing cost, and optimization effect of the algorithm. The model is applied to four countries, China, Chile, Mexico, and Japan, and the oil consumption data of the four countries are taken as the effectiveness analysis of the model. The optimized grey Bernoulli model NGBM(1,1) is compared with the other six grey prediction models, which all show better results. So, the model is used to predict oil consumption in four countries over the next five years.

The remainder sections are organized as follows. Section 2 establishes the optimized grey Bernoulli NGBM(1,1). Section 3 analyzes the validity of the model by using the energy data of four countries. Section 4 forecasts the oil consumption of four countries over the next five years. Section 5 provides the conclusion.

2. Grey Bernoulli Extension Model ONGBM(1,1)

In this section, firstly, the grey Bernoulli model NGBM (1,1) is summarized. According to the grey action of the model and the parameters of the model nonlinearity, the model is extended into a new grey Bernoulli extended model ONGBM(1,1,k,c), and the properties of the model are studied.

2.1. Optimized Grey Bernoulli Model ONGBM (1,1). The original sequence is

$$X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)). \quad (1)$$

The first-order accumulating generation sequence is defined as

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)), \quad (2)$$

where $x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i)$, ($k = 1, 2, \dots, n$).

$Z^{(1)}$ is adjacent to the mean generation sequence of $X^{(1)}$:

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)), \quad (3)$$

where

$$z^{(1)}(k) = 1/2x^{(1)}(k) + 1/2x^{(1)}(k-1), (k = 2, 3, \dots, n).$$

Definition 1. The sequences $X^{(0)}$, $X^{(1)}$, and $Z^{(1)}$ are as shown in equations (1)–(3), so

$$x^{(0)}(k) + az^{(1)}(k) = b(x^{(1)}(k))^\gamma. \quad (4)$$

It is called the grey Bernoulli model and it is abbreviated as NGBM(1,1) model [23], and the whitening equation has the following forms:

$$\frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = b(x^{(1)}(t))^\gamma, \quad (5)$$

where γ is a real number.

The time response of the NGBM(1,1) model is given by

$$\hat{x}^{(1)}(k) = \left\{ \left[\left(x^{(0)}(1) \right)^{1-\gamma} - \frac{b}{a} \right] e^{-a(k-1)(1-\gamma)} + \frac{b}{a} \right\}^{1/(1-\gamma)}, \quad k = 2, 3, \dots, n. \quad (6)$$

The reducing value of $x^{(0)}(k)$ is

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \quad k = 2, 3, \dots, n. \quad (7)$$

The background value in Definition 1 is defined as follows [24]:

$$z^{(1)}(k) = (1 + \beta)x^{(1)}(k) - \beta x^{(1)}(k-1), \quad \beta \in (-1, +\infty). \quad (8)$$

So, the model is defined as follows.

Definition 2. The sequences $X^{(0)}$, $X^{(1)}$, and $Z^{(1)}$ are as shown in equations (1), (2), and (8), so

$$x^{(0)}(k) + az^{(1)}(k) = b(z^{(1)}(k))^{\gamma}. \quad (9)$$

It is the optimized model of the grey Bernoulli model and is called ONGBM(1,1) model for short.

The parameters a and b of the ONGBM(1,1) model are as follows:

$$(a, b)^T = (B^T B)^{-1} B^T Y, \quad (10)$$

where the matrices B and Y are

$$B = \begin{pmatrix} -z^{(1)}(2) & (z^{(1)}(2))^{\gamma} \\ -z^{(1)}(3) & (z^{(1)}(3))^{\gamma} \\ \vdots & \vdots \\ -z^{(1)}(n) & (z^{(1)}(n))^{\gamma} \end{pmatrix}, \quad (11)$$

$$Y = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix}.$$

The reduction function is given by equations (6) and (7).

2.2. Optimization of ONGBM(1,1) Model by the Simulated Annealing Algorithm. The idea of the simulated annealing algorithm (hereinafter referred to as SA) was first proposed by Metropolis et al. In 1983, Kirkpatrick et al. used it for combinatorial optimization and VLSI design. SA to solve combinatorial optimization problem is based on the similarity between solid material annealing process in physics and general combinatorial optimization problem. When a solid substance is annealed, it is usually warmed and melted first, so that the particles can move freely. Then, as the temperature drops, the particles also gradually form a lattice of low energy. If the temperature near the condensation point drops slowly enough, the solid must form the lowest energy ground state.

The specific steps of SA to solve the model are as follows.

Step 1. Initialization: for general data (not big fluctuations), set the variation range of β as $(-1, 1)$. An initial solution β_0 is selected at random within this range, and the corresponding target value $\varepsilon(\beta_0)$ is calculated. Set the initial temperature as T_0 and the ending temperature as T_f , generate a random number $\alpha \in (0, 1)$ as the threshold, the cooling law: $T(t+1) = V \cdot T(t)$, $V \in (0, 1)$ is the annealing coefficient, and t is the t th iteration. Since T must be reduced slowly, V should be a number close to 1. Finally, convergence conditions are set according to actual requirements, such as the magnitude of error, number of iterations, or ending temperature. If the data are large fluctuation data, the variation range of β is set as $(-1, 1)$.

Step 2. At temperature T , another point β' in the neighborhood of the current solution β is selected as the new solution, and the difference between the objective function value $\varepsilon(\beta)$ and $\varepsilon(\beta')$ is calculated, $\Delta\varepsilon = \varepsilon(\beta) - \varepsilon(\beta')$.

Step 3. When $\Delta\varepsilon < 0$, it means that the new solution β' is accepted; when $\Delta\varepsilon > 0$, it means that the new solution β' is accepted according to probability $p = \exp(-(\Delta\varepsilon/T))$; and if $p > \alpha$, then the new solution β' is accepted, and $\beta = \beta'$.

Step 4. Following the cooling rule: $T(t+1) = V \cdot T(t)$, the temperature is lowered.

Step 5. Repeat Steps 2–4 until the convergence condition is satisfied.

3. Verification of ONGBM(1,1) Model

This section is mainly divided into three parts. The first part describes the evaluation indicators mainly adopted in this research. In order to measure the effectiveness of the model, two evaluation indicators APE and MAPE are quoted in the research process, and the calculation method is given in Section 3.1. In the second part, the model ONGBM(1,1) is applied to the data from different countries for verification, and the simulation results are compared and analyzed with the existing grey univariate models, including NGBM(1,1), Verhulst, GM(1,1), NGM(1,1), TDGM(1,1), and ARG(1,1) models. Meanwhile, the APE trend comparison diagram and MAPE comparison diagram of different cases have been given in Section 3.2. In the third part, based on the cases in the second part, the annual oil consumption in different regions in the next five years is predicted and analyzed. In the following example analysis, the calculation

TABLE 1: Metrics of models for fitting in Case 1.

Year	Raw data	ONGBM (1,1)	APE (%)	NGBM (1,1)	APE (%)	GM (1,1)	APE (%)	NGM (1,1)	APE (%)	TDGM (1,1)	APE (%)	Verhulst	APE (%)	AR-GM (1,1)	APE (%)
1999	213.7	213.7000	0	213.7000	0	213.7000	0	213.7000	0	213.7000	0	213.7000	0	213.7000	0
2000	228.8	215.0852	-5.9942	212.7806	-7.0015	232.9317	-1.8058	208.0514	-9.0684	219.8465	3.9133	72.66238	-68.2420	231.0545	0.9854
2001	234.0	243.8493	4.2091	241.1982	3.0762	248.7854	-6.3186	230.602	-1.4522	242.3371	3.5628	95.60745	-59.1421	249.255	6.5192
2002	252.7	268.6015	6.2926	265.726	5.1547	265.7182	-5.1516	253.0378	0.1337	264.7132	4.7539	124.4687	-50.7445	268.3428	6.1903
2003	281.3	291.4472	3.6073	288.4105	2.5277	283.8034	-0.8900	275.3594	-2.1118	286.9755	2.0176	159.8201	-43.1852	288.3612	2.5102
2004	328.5	313.3144	-4.6227	310.1574	-5.5837	303.1196	7.7262	297.5674	-9.4163	309.1244	5.8982	201.6125	-38.6263	309.3555	-5.8279
2005	334.3	334.7051	0.1212	331.4585	-0.8500	323.7504	3.1557	319.6625	-4.3786	331.1607	0.9391	248.7314	-25.5963	331.3732	-0.8755
2006	359.2	355.928	-0.9109	352.6165	-1.832827	345.7855	3.73456	341.6451	-4.8872	353.0848	1.7024	298.5667	-16.8801	354.4644	-1.3184
2007	377.0	377.1903	0.0505	373.8355	-0.8394	369.3202	2.0371	363.5158	-3.5767	374.8974	0.5577	346.8195	-8.0054	378.6812	0.4459
2008	384.7	398.6414	3.6240	395.2631	2.7458	394.4568	-2.5362	385.2752	0.1495	396.599	3.0931	387.8443	0.8173	404.0787	5.0373
2009	400.6	420.3955	4.9415	417.0120	4.0969	421.3042	-5.1683	406.9239	1.5786	418.1901	4.3909	415.7108	3.7720	430.7143	7.5173
2010	455.5	442.5437	-2.8444	439.1731	-3.5844	449.9789	1.2121	428.4625	-5.9358	439.6714	3.4750	425.8055	-6.5191	458.6484	0.6912
MAPE _{FIT} (%)			3.3835		3.3903		3.6124		3.8808		3.1185		29.2300		3.4471
2011	472.4	465.1620	-1.5322	461.8220	-2.2392	480.6053	-1.7369	449.8914	-4.7647	461.0433	2.4040	416.3413	-11.8668	487.9443	3.2905
2012	495.3	488.3161	-1.4100	485.0246	-2.0746	513.3161	-3.6374	471.2113	-4.8635	482.3065	2.6234	388.9955	-21.4626	518.6684	4.7180
2013	517.3	512.0644	-1.0121	508.8396	-1.6355	548.2533	-5.9836	492.4227	-4.8091	503.4615	2.6751	348.3102	-32.6677	550.8903	6.4934
2014	539.3	536.4604	-0.5265	533.3208	-1.1087	585.5684	-8.5793	513.5262	-4.7791	524.5088	2.7427	300.1995	-44.3354	584.6831	8.4152
2015	573.3	561.5537	-2.0489	558.5185	-2.5783	625.4232	-9.0918	534.5223	-6.7640	545.4491	4.8580	250.3389	-56.3337	620.1233	8.1673
2016	587.0	587.3918	0.0667	584.4808	-0.4292	667.9906	-13.7974	555.4115	-5.3813	566.2827	3.5293	203.0806	-65.4037	657.2912	11.9747
2017	610.7	614.0203	0.5437	611.2542	0.0907	713.4552	-16.8258	576.1944	-5.6502	587.0104	3.8791	161.089	-73.6222	696.2711	14.0120
2018	641.2	641.4836	0.0442	638.8841	-0.3612	762.0142	-18.8419	596.8716	-6.9133	607.6326	5.2351	125.5214	-80.4240	737.1513	14.9643
MAPE _{PRE} (%)			0.8981		1.3147		9.8118		5.4906		3.4933		48.2645		9.0044

FIGURE 1: Overall APE comparison of seven models in Case 1.

process of the ONGBM(1,1) model is implemented in accordance with the steps described in Section 2.2.

3.1. Model Evaluation Indexes. The model evaluation indexes adopt the APE and MAPE that are commonly used in the grey model, and the specific calculation formulas are shown as equations (12) and (13). In the comparison

process, the smaller the calculated values of APE and MAPE, the better the model effect. The calculation of MAPE is divided into two parts in this study, including $MAPE_{FIT}$ of the fitting part and $MAPE_{PRE}$ of the prediction part. These two evaluation indexes should be comprehensively considered in the evaluation process of the model.

$$APE = \left(\frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right) \times 100\%, \quad k = 1, 2, 3, \dots, n. \quad (12)$$

$$MAPE = \frac{1}{n-1} \left(\sum_{i=1}^n \left| \frac{x^{(0)}(k) - \hat{x}^{(0)}(k)}{x^{(0)}(k)} \right| \right) \times 100\%, \quad k = 1, 2, 3, \dots, n. \quad (13)$$

3.2. Case Analysis. In order to illustrate the effectiveness of the model, this section applies the optimized NGBM(1,1) model to the oil data of four countries, respectively, and verifies the effectiveness of the model from different regions, which included the annual oil consumption data for China, Chile, Mexico, and Japan, and the data based on the BP Statistical Review of World Energy.

3.2.1. Case 1: Annual Oil Consumption of China. China is the most populous developing country and the second largest economy in the world. With the rapid development of China, the social productivity of China was significantly enhanced, and at the same time, the energy consumption ability also constantly improved, while nonfossil energy

sources such as coal and oil are still the main energy sources in China currently. According to the data released by the National Bureau of Statistics of China, during the development process of China, there has been an obvious gap between the value of energy produced and the value of energy consumption and there has been a situation of short supply. Therefore, part of the energy begins to rely on imports; among them, oil accounts for a large proportion of imported energy. Therefore, the security of oil supply and demand is a problem that China needs to consider in the current development process.

In this paper, the oil consumption data from 1999 to 2018 in China were selected for model building, in which the data from 1999 to 2010 were used to establish the model and train the optimal parameter values, and the optimal

FIGURE 2: Overall APE comparison after removing the Verhulst model in Case 1.

FIGURE 3: Comparison of MAPE in Case 1.

parameter values $r = 0.174$ and $m = 0.593$ are calculated. Then the data from 2011 to 2018 were used to verify the validity of the model. The simulation results and APE of the different models are shown in Table 1.

As can be seen in Table 1, the Verhulst model shows poor performance in both the simulation and prediction parts. Except for the Verhulst model, the remaining six models show no significant difference in the fitting part, and the APE all fluctuated at about 3.5%. However, in the prediction part, although the prediction results of the GM(1,1), NGM(1,1), and AR-GM(1,1) models are all below 10%, while

they are higher than 5%, compared with the other three models, and the deviation is relatively obvious. Then among the ONGBM(1,1), NGBM(1,1), and TDGM(1,1) models, the accuracy of the optimized NGBM(1,1) model is higher, and its $MAPE_{PRE}$ reaches 0.8981%, less than 1%, and that compared with the unoptimized model, the original prediction accuracy is improved by 0.4166%.

Figure 1 shows the APE comparison chart in Case 1. It can be clearly seen that the Verhulst model shows poor performance in the application of these data, so the results of the Verhulst model have a greater impact on the overall

TABLE 2: Metrics of models for fitting in Case 2.

Year	Raw data	ONGBM (1,1)	APE (%)	NGBM (1,1)	APE (%)	GM (1,1)	APE (%)	NGM (1,1)	APE (%)	TDGM (1,1)	APE (%)	Verhulst	APE (%)	AR-GM (1,1)	APE (%)
2004	12.4	12.4	0	12.4	0	12.4	0	12.4	0	12.4	0	12.4	0	12.4	0
2005	12.9	13.2328	2.5796	13.9921	8.4659	15.2246	-18.0201	7.8722	-38.9750	12.7664	1.0358	6.4967	-49.6382	14.5834	13.0500
2006	14.4	15.0446	4.4766	15.8268	9.9086	15.7179	-9.1522	13.6896	-4.9336	15.9771	10.9519	9.3351	-35.1732	15.9538	10.7902
2007	18.5	16.2433	-12.1984	16.9431	-8.4157	16.2272	12.2853	16.2658	-12.0767	17.3294	6.3274	12.7894	-30.8684	16.8138	-9.1144
2008	19.2	17.0617	-11.1369	17.6239	-8.2089	16.7530	12.7446	17.4067	-9.3400	17.8991	6.7758	16.4237	-14.4598	17.3536	-9.6166
2009	18.7	17.6170	-5.7917	18.0100	-3.6901	17.2959	7.5087	17.912	-4.2141	18.1390	3.0001	19.4232	3.8671	17.6924	-5.3884
2010	16.6	17.9785	8.3043	18.1844	9.5445	17.8563	-7.5682	18.1357	9.2513	18.2400	9.8797	20.8529	25.6197	17.9050	7.8614
2011	18.1	18.1921	0.5086	18.205	0.5609	18.4349	-1.8504	18.2348	0.7448	18.2826	1.0088	20.1871	11.5308	18.0384	-0.3402
2012	18.1	18.2896	1.0474	18.0992	-0.0042	19.0322	-5.1506	18.2787	0.9873	18.3005	1.1079	17.6770	-2.3373	18.1222	0.1225
MAPE _{FIT} (%)			5.7554		6.0998		9.2850		10.0653		5.0109		21.6868		7.0355
2013	17.5	18.2946	4.5406	17.9052	2.3154	19.6490	-12.2798	18.2981	4.5607	18.3081	4.6176	14.1695	-19.0316	18.1747	3.8556
2014	17.0	18.2251	7.2062	17.6402	3.7660	20.2856	-19.3273	18.3067	7.6867	18.3113	7.7133	10.5746	-37.7964	18.2077	7.1042
2015	17.1	18.0949	5.8180	17.3204	1.2891	20.9430	-22.4734	18.3105	7.0792	18.3126	7.0912	7.4784	-56.2670	18.2284	6.5989
2016	18.2	17.9152	-1.5646	16.9585	-6.8215	21.6216	-18.7998	18.3122	0.6167	18.3132	0.6218	5.0897	-72.0347	18.2414	0.2275
2017	17.7	17.6952	-0.0273	16.5645	-6.4154	22.3222	-26.1140	18.313	3.46318	18.3134	3.4656	3.3742	-80.9367	18.2496	3.1049
2018	18.1	17.4421	-3.6349	16.1466	-10.7924	23.0455	-27.3231	18.3133	1.1785	18.3135	1.1796	2.1982	-87.8555	18.2547	0.8546
MAPE _{PRE} (%)			3.7986		5.2333		21.0529		4.0975		4.1148		58.9870		3.6243

FIGURE 4: Overall APE comparison of seven models in Case 2.

comparison effect of all models. Then the comparison chart that removed the calculated data of the Verhulst model is drawn as shown in Figure 2.

In Figure 2, it can be seen that the relative error in the prediction part fluctuates within a small range, among which the NGM(1,1) model has a few large deviations at some points. However, the overall relative error of NGM(1,1) of both simulation and prediction parts is in a relatively stable state. In the prediction part shown in Figure 2, it can also be seen that the relative errors of GM(1,1) and AR-RM(1,1) models show a trend of a gradual rise, and the deviation is gradually larger.

Figure 3 shows the MAPE comparison of the seven models in Case 1, which can more intuitively see the performance difference between different models. The overall level of the fitting part is similar except for the Verhulst model while the ONGBM(1,1) model has more advantages in the prediction part.

3.2.2. Case 2: Annual Oil Consumption of Chile. Chile is the longest and narrowest country in the world, which is rich in mineral resources, but short of energy. The production of coal, oil, and natural gas in Chile is low and mainly depends on imports from other countries. Chile is not a populous country, and thus, the import volume will fluctuate greatly with the demand of the country. Therefore, it can be seen from Table 2 that the annual oil consumption data of Chile fluctuated to a certain extent. In this case, the oil consumption data of Chile from 2004 to 2018 were selected for analysis. The original data and the calculated data of seven models are shown in Table 2. The data from 2004 to 2012 were used to establish the model, and the data from 2013 to 2018 were used to test the validity of the model.

It can be seen from the calculation results in Table 2 that, in the fitting part, the effects of ONGBM(1,1), NGBM(1,1), and TDGM(1,1) are closer, and the effect of TDGM(1,1) is slightly better than that of the optimized NGBM(1,1) model, and the accuracy of ONGBM(1,1) is 0.3444% higher than that of the unoptimized NGBM(1,1) model. In the prediction part, the AR-GM(1,1) model has the best effect, and compared with ONGBM(1,1) model, the $MAPE_{PRE}$ of the AR-GM(1,1) model was 0.1743% higher, but the fitting error of the AR-GM(1,1) model is relatively higher than that of ONGBM(1,1) model. Although the $MAPE_{FIT}$ and $MAPE_{PRE}$ of the ONGBM(1,1) model are not optimal in this case, the comprehensive consideration shows that the ONGBM(1,1) model still has certain desirability, and the $r = 0.287$ and $m = 0$ can be calculated in this case.

In the APE comparison shown in Figure 4, it can be seen that the APE of the Verhulst model in the prediction part is obviously larger than that of other models, and from the calculation results of Table 3, it can be known that its $MAPE_{PRE}$ has reached 58.9870%, which led the selection of the error interval too large in the process of mapping and then affected the comparison effect of other models. Therefore, in this case, the relative error value of the Verhulst model is removed and the APE comparison chart is redrawn, as shown in Figure 5.

It can be seen in Figure 5 that the fitting error of the NGM(1,1) model in 2005 was obviously higher, and there was an abnormality at one point, and then, the subsequent nodes tended to be stable. In the fitting part, before 2010, the errors of the seven models were relatively obvious, and the fluctuation range was relatively large. After 2011, except for the GM(1,1) and NGBM(1,1) models, the relative errors of the other models showed no obvious abnormal changes and were relatively stable.

TABLE 3: Metrics of models for fitting in Case 3.

Year	Raw data	ONGBM (1,1)	APE (%)	NGBM (1,1)	APE (%)	GM (1,1)	APE (%)	NGM (1,1)	APE (%)	TDGM (1,1)	APE (%)	Verhulst	APE (%)	AR-GM (1,1)	APE (%)
1999	87.1	87.1	0	87.1	0	87.1	0	87.1	0	87.1	0	87.1	0	87.1	0
2000	91.2	81.9017	-10.1955	80.1035	-12.1672	89.1865	2.2078	84.6546	-7.1770	88.4599	3.0045	24.3087	-73.3457	89.4691	-1.8980
2001	89.7	87.9096	-1.9960	86.1203	-3.9907	89.7028	-0.0031	85.8011	-4.3466	89.3157	0.4284	30.4944	-66.0040	90.9500	1.3935
2002	85.7	91.5129	6.7828	89.8657	4.8608	90.2221	-5.2766	86.8598	1.3534	90.1060	5.1412	37.8939	-55.7830	91.8757	7.2062
2003	88.0	93.7467	6.5304	92.3067	4.8940	90.7444	-3.1186	87.8376	-0.1845	90.8359	3.2226	46.5390	-47.1148	92.4545	5.0619
2004	91.6	95.0866	3.8063	93.8903	2.5003	91.2697	0.3606	88.7406	-3.1216	91.5099	0.0984	56.3387	-38.4948	92.8162	1.3277
2005	93.8	95.7964	2.1284	94.8653	1.1357	91.7981	2.1342	89.5745	-4.5048	92.1323	1.7779	67.0245	-28.5453	93.0424	-0.8077
2006	92.8	96.0402	3.4916	95.3867	2.7874	92.3295	0.5070	90.3447	-2.6458	92.7071	0.1001	78.1046	-15.8355	93.1837	0.4135
2007	96.4	95.9279	-0.4897	95.5584	-0.8731	92.8640	3.6680	91.0559	-5.5437	93.2379	3.2802	88.8524	-7.8294	93.2721	-3.2447
2008	96.2	95.5373	-0.6888	95.4540	-0.7755	93.4017	2.9089	91.7127	-4.6645	93.7280	2.5696	98.3542	2.2392	93.3273	-2.9861
2009	92.9	94.9256	2.1804	95.1278	2.3981	93.9424	-1.1220	92.3193	-0.6251	94.1807	1.3785	105.6322	13.7053	93.3619	0.4972
2010	93.3	94.1363	0.8964	94.6212	1.4161	94.4862	-1.2714	92.8795	-0.4507	94.5987	1.3919	109.8311	17.7182	93.3834	0.0894
2011	94.9	93.2032	-1.7880	93.9663	-0.9838	95.0332	-0.1404	93.3968	-1.5840	94.9847	0.0892	110.4153	16.3491	93.3969	-1.5838
2012	96.4	92.1533	-4.4053	93.1889	-3.3310	95.5834	0.8471	93.8746	-2.6198	95.3412	1.0984	107.3079	11.3153	93.4054	-3.1065
2013	93.8	91.0081	-2.9764	92.3096	-1.5889	96.1367	-2.4912	94.3158	0.5499	95.6704	1.9940	100.9113	7.5813	93.4107	-0.4151
MAPE _{FIT} (%)			3.4540		3.1216		1.8612		2.8122		1.8268		28.7044		2.1451
2014	89.5	89.7856	0.3191	91.3456	2.0621	96.6933	-8.0372	94.7232	5.8360	95.9744	7.2339	92.0010	2.7944	93.4139	4.3731
2015	88.5	88.5004	0.0004	90.3111	2.0464	97.2530	-9.8904	95.0995	7.4571	96.2551	8.7628	81.5382	-7.8665	93.4160	5.5548
2016	89.1	87.1648	-2.1720	89.2179	0.1323	97.8160	-9.7823	95.4470	7.1235	96.5143	8.3214	70.4734	-20.9052	93.4173	4.8454
2017	85.8	85.7891	-0.0127	88.0761	2.6528	98.3823	-14.6647	95.7680	11.6177	96.7538	12.7666	59.6004	-30.5357	93.4181	8.8789
2018	82.8	84.3822	1.9108	86.8944	4.9449	98.9519	-19.5071	96.0643	16.0197	96.9748	17.1194	49.4852	-40.2353	93.4186	12.8244
MAPE _{PRE} (%)			0.8830		2.3677		12.3763		9.6108		10.8408		20.4674		7.2953

FIGURE 5: Overall APE comparison after removing the Verhulst model in Case 2.

FIGURE 6: Comparison of MAPE in Case 2.

In order to see the MAPE comparison of the different models in Table 2 intuitively, Figure 6 presents the MAPE comparison diagram of the simulation part and prediction part, through that the comparison effect is more obvious.

3.2.3. Case 3: Annual Oil Consumption of Mexico. Mexico is rich in oil and gas resources and is one of the largest oil producers in the world. EIA data show that the crude oil production of Mexico has shown a downward trend since 2010, and corresponding to the “BP Statistical Review of World Energy” data released by BP, it can be seen that the oil

consumption data of Mexico have shown a gradual decrease since 2007. This paper selects the oil consumption data of Mexico from 1999 to 2018. The original data of Mexico’s annual oil consumption and the simulation data of the ONGBM(1,1) model and the other comparison models are given in Table 1. Then, the data from 1999 to 2013 are used to build the model and calculate the model parameters, and the data from 2014 to 2018 are used to test the validity of the model.

The oil consumption data of Mexico are substituted into the model, and the optimal parameters of the ONGBM(1,1) model are calculated by the simulated annealing algorithm, and then $r = 0.185$ and $m = 0.939$. From the calculation results of the

FIGURE 7: Overall APE comparison of seven models in Case 3.

FIGURE 8: Overall APE comparison after removing the Verhulst model in Case 3.

ONGBM(1,1) model and the other six comparison models in Table 1, it can be seen that, except for the Verhulst model, all other models exhibit higher accuracy in the fitting process, among which the $MAPE_{FIT}$ of the GM(1,1), NGM(1,1), TDGM(1,1), and AR-GM(1,1) model are all lower than 3%, and there was no significant difference between them, and it is slightly higher than that of the ONGBM(1,1) and NGBM(1,1) models in the process of fitting. And the best performance in the simulation part is shown by the TDGM(1,1) model, whose $MAPE_{FIT}$ reaches 1.8268%. In the prediction part, the Verhulst model also shows poor results compared with other models,

while GM(1,1) and TDGM(1,1) models showed a slightly poor performance in the prediction part, with $MAPE_{PRE}$ higher than 10%, and the prediction errors of the NGM(1,1) and AR-GM(1,1) models are below 10%, while there is a slight deviation compared with the ONGBM(1,1) model. The comparison between ONGBM(1,1) and NGBM(1,1) shows that the accuracy of the optimized model in the fitting effect is slightly increased by 0.3324%, but the prediction error is significantly improved, which reaches less than 1%, reflecting the better performance.

In order to see the comparison calculation results in Table 1 more intuitively, Figure 7 shows the APE

FIGURE 9: Comparison of MAPE in Case 3.

comparison diagram of seven models. It can be clearly seen that the deviation of the Verhulst model is very large, and the largest deviation of which reached more than 70%, because the error of the Verhulst model is too large and the value of the vertical axis of the image is increased, making the contrast effect of other models not obvious, and therefore, Figure 8 shows the contrast effect after removing the Verhulst model.

It can be seen from Figure 7 that the fitting errors of the first four points of the ONGBM(1,1) model fluctuate greatly in the fitting part and tend to be stable in the subsequent nodes. In the fitting part, the relative errors of most nodes of the seven models fluctuate less than 5% after the fifth time node. In the prediction part, the APE of GM(1,1) was significantly increased by node, while the relative error of ONGM(1,1) and ONGBM(1,1) models fluctuated around 2% in this part, and ONGBM(1,1) showed a better effect.

The comparison of the MAPE values of the seven models in the simulation and prediction part is shown in Figure 9, and the effects of each model can be clearly distinguished from the figure.

3.2.4. Case 4: Annual Oil Consumption in Japan. Japan is a highly developed capitalist country, which is located on an island in East Asia. Because the domestic resources in Japan are relatively scarce and the proven oil reserves are limited, its energy is mainly dependent on imports. However, as the third largest economy in the world, Japan has become the world's fifth largest oil consumer after the United States, China, India, and Russia. Japan is also the fourth largest crude oil importer after the United States, China, and India. Therefore, the analysis and forecast of oil consumption in Japan are particularly important. According to the data from "BP Statistical Review of World Energy," annual oil consumption of Japan has shown a

downward trend since 2012, which is closely related to the aging of the country's internal population, the decline of the population, and the improvement of energy efficiency by Japanese domestic technology. This case selects the data from 2008 to 2018 to build the model and evaluates the validity of the model. The data from 2008 to 2012 are used to build the model, and the data from 2013 to 2018 are used to verify the validity of the model. The original data and simulation data of the seven models are shown in Table 4.

From the results shown in Table 4, it can be observed that the NGM(1,1) model has the largest deviation in the fitting part. The ONGBM(1,1), NGBM(1,1), GM(1,1), and AR-GM(1,1) models have similar performance effects, but the effect of ONGBM(1,1) is slightly better than the other three models. Substituting the data in Case 4 into the Verhulst model, it can be found that the fitting part showed good results. The $MAPE_{FIT}$ value was less than 10%, but its prediction error was about 65%, and the prediction performance was poor. In fact, except for the ONGBM(1,1) model and NGBM(1,1) model, the prediction error of other models exceeds 10%. But on the whole, the prediction effect of the optimized NGBM(1,1) model has been significantly improved, and the $MAPE_{FIT}$ value has increased by 2.997%. The parameters corresponding to the optimized ONGBM(1,1) are $r = 0.175$ and $m = 0.773$.

It can be seen from Figure 10 that, except for the large deviation of the Verhulst and the NGM(1,1) model in 2010, the relative error of the other years presents a relatively stable state. In fact, it can be known from the calculation results of Table 4 that the $MAPE_{PRE}$ of the Verhulst model reached 68.4851%. It can also be seen in the comparison chart of Figure 10 that in the prediction part, the relative error value of the Verhulst model shows a gradually increasing trend. Because the error calculated by it is too large and affects the comparison effect of other models, the comparison result

TABLE 4: Metrics of models for fitting in Case 4.

Year	Raw data	ONGBM (1,1)	APE (%)	NGBM (1,1)	APE (%)	GM (1,1)	APE (%)	NGM (1,1)	APE (%)	TDGM (1,1)	APE (%)	Verhulst	APE (%)	AR-GM (1,1)	APE (%)
2008	208.2061	208.2	0	208.2	0	208.2061	0	208.2061	0	208.2061	0	208.2	0	208.2061	0
2009	210.516	211.2094	0.3370	207.897	-1.2366	211.3859	-0.4132	157.4182	-25.2227	209.8949	0.2951	159.7675	-24.1010	215.0505	2.1540
2010	211.032	218.3389	3.4781	216.5369	2.6241	213.9545	-1.3848	187.5574	-11.1237	215.0468	1.9024	219.7777	4.1600	215.3288	2.0361
2011	224.8901	218.4848	-2.8525	218.4805	-2.8544	216.5543	3.7066	203.2692	-9.6140	217.6672	3.2118	241.2857	7.2858	215.3401	-4.2465
2012	214.6511	215.0810	0.1775	216.9167	1.0325	219.1857	-2.1125	211.4598	-1.4868	219.0000	2.0260	207.317	-3.4387	215.3406	0.3212
MAPE _{FIT} (%)			1.7113		1.9369		1.9043		11.8618		1.8588		9.7464		2.1894
2014	204.0364	209.6452	2.7672	213.2665	4.5424	221.8490	-8.7301	215.7296	5.7310	219.6779	7.6660	143.8108	-29.5045	215.3406	5.5403
2015	196.5073	202.9962	3.3059	208.3029	6.0065	224.5448	-14.2679	217.9555	10.9147	220.0227	11.9667	85.5894	-56.4431	215.3406	9.5840
2016	190.96	195.6266	2.4223	202.4959	6.0188	227.2733	-19.0162	219.1159	14.7444	220.1980	15.3111	46.3702	-75.7224	215.3406	12.7674
2017	187.8064	187.8537	0.0286	196.1525	4.4475	230.0349	-22.4852	219.7208	16.9933	220.2872	17.2949	23.8493	-87.3007	215.3406	14.6610
2018	182.3648	179.8905	-1.3758	189.4826	3.8830	232.8301	-27.6727	220.0361	20.6571	220.3326	20.8197	11.9385	-93.4548	215.3406	18.0823
MAPE _{PRE} (%)			1.9800		4.9797		18.4344		13.8081		14.6117		68.4851		12.1270

FIGURE 10: Overall APE comparison of seven models in Case 4.

FIGURE 11: Overall APE comparison after removing the Verhulst model in Case 4.

after removing the relative error data of the Verhulst model is shown in Figure 11.

In the APE comparison chart shown in Figure 11, it can be clearly seen that the relative errors calculated by the GM(1,1), NGM(1,1), TDGM(1,1), and AR-GM(1,1) models are gradually increasing in the prediction part, and each model showed the best performance in 2013. Moreover, the ONGBM(1,1) model is indeed better than other models.

The comparison of the MAPE values of the seven models in the simulation and prediction part is shown in Figure 12,

and the effects of each model can be clearly distinguished from the figure.

4. Application of the ONGBM(1,1) Model

Based on the modelling analysis in Section 3.2, this paper predicts the oil consumption of the above four countries in the next five years, and the forecast data are shown in Table 5.

It can be analyzed from the forecast results in Table 5 that the annual oil consumption of most countries in the next five years will still show a continuous downward trend. However,

FIGURE 12: Comparison of MAPE in Case 4.

TABLE 5: Forecast results of oil consumption in the four countries in the next 5 years.

Year	Country			
	Mexico	Chile	China	Japan
2019	82.9514	17.1622	669.8260	164.3109
2020	81.5033	16.8605	699.0912	155.9098
2021	80.0434	16.5415	729.3230	147.7182
2022	78.5763	16.2089	760.5658	139.7819
2023	77.1063	15.8656	792.8642	132.1313

China is the most populous country in the world, which is in a stage of full-speed development currently. Although it has to take the initiative to adjust its energy structure, due to its large population, vast areas of economic development, and too many related factors, it will often be implemented after the policy is implemented. At the same time, since coal is the first energy source in China, reducing the dependence on coal is a major goal of China. Therefore, the consumption of oil as a substitute for coal may still increase; Chile is an energy-scarce country; in recent years, as the world gradually began to adjust its state of energy structure, Chile also established its own policy because Chile belongs to small population, and thus, the implementation of measures can see the effect relatively quickly. Therefore, the country may have a downward trend in its annual oil consumption under the current environment of energy restructuring. The oil production of Mexico has been declining since 2010, and its annual oil consumption has been declining year by year since 2007; the resources in Japan are relatively scarce, and it mainly depends on imports, and the data show that the oil consumption of Japan has shown a downward trend since 2012. Based on the above reasons and the forecast results of annual oil consumption in the next five years, it can be concluded that oil consumption is on a downward trend in most countries.

5. Conclusion

This paper optimizes the background value of the NGBM(1,1) model and proposes the ONGBM(1,1) model on this basis, and the simulated annealing algorithm was used to optimize undetermined coefficients in the NGBM(1,1) model. Actual oil consumption data from four countries, China, Chile, Mexico, and Japan, were used to test the effectiveness of the model. The results show that the optimized ONGBM(1,1) model is basically better than the other six grey prediction models. At the same time, applying the model to the oil consumption forecasts of the above four countries, it can be concluded that the oil consumption of the other three countries is showing a downward trend, except for China. This phenomenon is related to different factors such as the development measures of the own country, geographic location, resource ownership, and the economic development status of the country.

In this paper, the background values of the NGBM(1,1) model were optimized considering the nonlinear structure of the energy system. The simulated annealing algorithm is used to find the optimal undetermined coefficients, and an optimized ONGBM(1,1) model is established. From the two perspectives of modelling mechanism and data applicability, the actual oil consumption data of China, Chile, Mexico, and

Japan were selected to analyze the validity of the model. The selected data contain three types, namely, the data with steady rise, the data with irregular fluctuation, and the data with gradual decline and fluctuation. The comparison results show that the new model has a good effect under the two indexes, and the effect of the optimized ONGBM(1,1) model is basically better than that of the other six grey prediction models. Therefore, on the basis of the modelling analysis in Section 3.2, the model is continued to be applied to the oil consumption forecast of these four countries in 2019–2023. The forecast results show that, except China, the oil consumption of the other three countries shows a downward trend. This phenomenon is related to different factors such as the country's development measures, geographical location, resource availability, and national economic development.

The optimization model proposed in this paper mainly considers the development trend of the variable itself and then research and analysis on it. The nonlinear characteristic of the energy system is considered in the research, but the influence of other factors on energy development is rarely considered. To a certain extent, this problem restricts the application range of the model, so how to solve this problem better considering the influence of other factors on variables will be the focus of our future work.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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