Research Article

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

Kai Xu,1 Xinyu Pang,2 and Huiming Duan2

1School of International Business and Management, Sichuan International Studies University, Chongqing 400031, China
2School of Science, Chongqing University of Posts and Telecommunications, Chongqing 400065, China

Correspondence should be addressed to Kai Xu; 99002142@sisu.edu.cn

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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 multivariate 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

\[ X^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)\}. \]  

(1)

The first-order accumulating generation sequence is defined as

\[ X^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\}, \]  

(2)

where \( x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), (k = 1, 2, \ldots, n) \). \( Z^{(1)} \) is adjacent to the mean generation sequence of \( X^{(1)} \):

\[ Z^{(1)} = \{z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\}, \]  

(3)

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

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

\[ x^{(0)}(k) + a z^{(1)}(k) = b(z^{(1)}(k))^γ. \]  

(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:

\[ \frac{dx^{(1)}(t)}{dt} + a x^{(1)}(t) = b(x^{(1)}(t))^γ, \]  

(5)

where \( γ \) is a real number.

The time response of the NGBM(1,1) model is given by
The reducing value of $x^{(0)}(k)$ is

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

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

1. **Initialization:** For general data (not big fluctuations), set the variation range of $\beta$ as $(-1, 1)$. An initial solution $\beta_0$ is selected at random within this range, and the corresponding target value $\epsilon(\beta_0)$ 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: $T(t + 1) = V(t)$, $V \in (0, 1)$ is the annealing coefficient, and $t$ is the iteration number. 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 $\beta$ is set as $(-1, 1)$.

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

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

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

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 ARGM(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
| Year | Raw data | ONGM (L1) | APE (%) | NGBM (L1) | APE (%) | GM (L1) | APE (%) | NGM (L1) | APE (%) | TDGM (L1) | APE (%) | Verhulst | APE (%) | AR-GM (L1) | APE (%) | MAPEFIT (%) | MAPEPRE (%) |
|------|----------|-----------|---------|-----------|---------|---------|---------|-----------|---------|-----------|---------|----------|---------|-----------|---------|-------------|------------|
| 1999 | 213.7000 | 213.7000  | 0       | 213.7000  | 0       | 213.7000| 0       | 213.7000  | 0       | 213.7000  | 0       | 213.7000 | 0       | 213.7000  | 0       |             | 3.3835     |
| 2000 | 215.0852 | 213.7000  | 5.9942  | 212.7806  | 7.0015  | 232.9317| 1.8058  | 208.0514  | 9.0684  | 219.8465  | 3.9133  | 72.66238 | 95.60745| 231.0545  | 0.9854    |             | 3.3903     |
| 2001 | 243.8493 | 241.1982  | 3.0762  | 248.7854  | 6.3186  | 230.602 | 1.4522  | 242.3371  | 3.5628  | 95.60745  | 59.1421 | 249.255  | 6.5192  | 309.3555  | 5.8279    |             | 3.4471     |
| 2002 | 268.6015 | 265.726  | 5.1479  | 265.7182  | 5.1516  | 253.0378| 0.1337  | 264.7132  | 4.7539  | 124.4687  | 50.7445 | 268.3428| 6.1903  | 349.6812  | 6.8378    |             | 3.5293     |
| 2003 | 291.4472 | 288.4105  | 2.5277  | 283.8034  | 0.8900  | 275.3594| 2.1118  | 296.9755  | 2.0176  | 159.8201  | 43.1852 | 288.3612| 2.5102  | 309.6074  | 5.8279    |             | 3.5737     |
| 2004 | 328.5045 | 321.1509  | 0.5583  | 320.492   | 0.5549  | 312.107 | 0.0271  | 325.4805  | 0.0271  | 214.0285  | 0.0271  | 328.5045| 0.0271  | 328.5045  | 0.0271    |             | 3.6124     |
| 2005 | 334.7051 | 331.4585  | 0.8500  | 323.7504  | 1.5557  | 319.6625| 0.4378  | 331.1607  | 0.9391  | 248.7314  | 25.5963 | 331.3732| 0.8755  | 331.3732  | 0.8755    |             | 3.6370     |
| 2006 | 295.9280 | 292.6165  | 0.8394  | 283.8034  | 4.8872  | 353.0848| 1.7024  | 298.5667  | 16.8801 | 354.4644  | 1.3184  | 288.3612| 2.5102  | 309.6074  | 5.8279    |             | 3.6812     |
| 2007 | 377.1903 | 373.8355  | 0.8394  | 369.3202  | 2.0371  | 365.5158| 3.5767  | 374.8974  | 0.5577  | 346.8195  | 8.0054  | 378.6812| 0.4459  | 378.6812  | 0.4459    |             | 3.7720     |
| 2008 | 384.7051 | 382.6240  | 2.7458  | 394.4568  | 2.5362  | 385.2752| 0.1495  | 396.599   | 3.9391  | 387.8443  | 0.8173  | 404.0787| 5.0373  | 404.0787  | 5.0373    |             | 3.8808     |
| 2009 | 400.6000 | 397.1020  | 2.5467  | 417.0120  | 2.0969  | 406.9239| 1.5786  | 418.1901  | 4.3909  | 415.7108  | 3.7720  | 371.7434| 7.5173  | 371.7434  | 7.5173    |             | 3.9471     |
| 2010 | 442.5447 | 439.1731  | 3.8544  | 449.9789  | 1.2121  | 428.4625| 5.9358  | 439.6714  | 3.4750  | 425.8055  | 6.5191  | 458.6484| 0.6912  | 458.6484  | 0.6912    |             | 3.9471     |

**Table 1:** Metrics of models for fitting 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.

\[
APE = \left( \frac{x^{(0)}(k) - \tilde{x}^{(0)}(k)}{x^{(0)}(k)} \right) \times 100\%, \quad k = 1, 2, 3, \ldots, n. \tag{12}
\]

\[
MAPE = \frac{1}{n-1} \left( \sum_{k=1}^{n} \frac{x^{(0)}(k) - \tilde{x}^{(0)}(k)}{x^{(0)}(k)} \right) \times 100\%, \quad k = 1, 2, 3, \ldots, n. \tag{13}
\]

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
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
| Year | Raw data | ONGBM (1,1) APE (%) | NGBM (1,1) APE (%) | GM (1,1) APE (%) | NGBM (1,1) APE (%) | TDGM (1,1) APE (%) | Verhulst APE (%) | AR-GM (1,1) APE (%) | MAPEFIT (%) | MAPEPRE (%) |
|------|----------|---------------------|---------------------|-----------------|-------------------|-------------------|------------------|------------------------|-------------|-------------|
| 2004 | 12.4     | 12.4                | 0                   | 12.4            | 0                 | 12.4              | 0                | 12.4                   | 5.7554      | 3.7986      |
| 2005 | 12.9     | 13.9921             | 8.4659              | 15.2246         | -18.0201          | 7.8722            | -38.9750         | 12.7664                | 6.4967      | 6.0998      |
| 2006 | 14.4     | 15.8268             | 9.9086              | 15.7179         | -9.1522           | 13.6896           | -4.9336          | 15.9771                | 10.9519     | 15.9385     |
| 2007 | 18.5     | 16.9431             | -8.4157             | 16.2272         | 12.2853           | 16.2658           | -12.0767         | 17.3294                | 6.3274      | 16.8138     |
| 2008 | 19.2     | 17.6239             | -8.2089             | 16.7530         | 12.7446           | 17.4067           | -9.3400          | 17.8991                | 6.7758      | 17.3536     |
| 2009 | 18.7     | 18.0100             | -3.6901             | 17.2959         | 7.5087            | 17.912             | -4.2141          | 18.1390                | 3.0001      | 17.6924     |
| 2010 | 16.6     | 18.1844             | 9.5445              | 18.7563         | -7.5682           | 18.1357           | 9.2513            | 18.2400                | 9.8797      | 20.8529     |
| 2011 | 18.1     | 18.205              | 0.5609              | 18.4349         | -1.8504           | 18.2348           | 0.7448            | 18.2826                | 1.0088      | 20.1871     |
| 2012 | 18.1     | 18.0992             | -0.0042             | 19.0322         | -5.1506           | 18.2787           | 0.9873            | 18.3005                | 1.1079      | 17.6770     |
|      |          |                     |                     |                 |                   |                   |                  |                        |             |             |
| MAPEFIT (%) | 5.7554 | 6.0998              | 9.2850              | 10.0653         |                   |                   |                  |                        |             |             |
|      |          |                     |                     |                 |                   |                   |                  |                        |             |             |
| 2013 | 17.5     | 18.2946             | 4.5406              | 19.7052         | 2.3154            | 19.6490           | -12.2798         | 18.2831                | 4.5607      | 4.6176      |
| 2014 | 17.0     | 18.2251             | 7.2062              | 17.6402         | 3.7660            | 20.2856           | -19.3273         | 18.3067                | 7.6867      | 7.7133      |
| 2015 | 17.1     | 18.0949             | 5.8180              | 17.3204         | 1.2891            | 20.9430           | -22.4734         | 18.3105                | 7.0792      | 7.0912      |
| 2016 | 18.2     | 17.9152             | -1.5646             | 16.9585         | -6.8215           | 21.6216           | -18.7998         | 18.3122                | 0.6167      | 0.6218      |
| 2017 | 17.7     | 17.6545             | -6.4154             | 16.3222         | -26.1140          | 18.3138           | 3.46318           | 18.3134                | 3.4656      | 3.3742      |
| 2018 | 18.1     | 17.4421             | -3.6349             | 16.1466         | -10.7924          | 23.0455           | -27.3231         | 18.3133                | 1.1785      | 1.1796      |
|      |          |                     |                     |                 |                   |                   |                  |                        |             |             |
| MAPEPRE (%) | 3.7986 | 5.2333              | 21.0529             | 4.0975          |                   |                   |                  |                        | 4.1148      | 58.9870     |
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 MAPEPRE 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 MAPEFIT and MAPEPRE 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 MAPEPRE 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 (%) | MAPEFIT (%) | MAPEPRE (%) |
|------|----------|---------------------|---------------------|------------------|------------------|-------------------|------------------|-------------------|-------------|-------------|
| 1999 | 87.1     | 87.1                | 0                   | 87.1             | 87.1             | 0                 | 87.1             | 0                 | 87.1        | 0           |
| 2000 | 91.2     | 81.9                | -10.1955            | 80.1035          | -12.1672         | 89.1865           | 2.078            | 84.6546          | 0.0034      | -7.1770     |
| 2001 | 89.7     | 87.9                | -1.960              | 86.1203          | -3.9907          | 89.7028           | -0.0031          | 85.8011          | 0.4346      | -4.3466     |
| 2002 | 85.7     | 91.5046             | 6.7828              | 89.8657          | 4.8608           | 90.2221           | -5.2766          | 86.8598          | 1.3534      | 90.1060     |
| 2003 | 88.0     | 93.7467             | 5.504              | 92.3067          | 4.8940           | 90.7428           | 0.0031           | 91.0559          | 0.0984      | 78.1046     |
| 2004 | 91.6     | 95.0866             | 3.8063              | 93.8903          | 3.0606           | 90.7428           | -3.1216          | 88.7406          | 5.8360      | 91.5099     |
| 2005 | 93.8     | 95.7964             | 2.1284              | 94.8653          | 1.1357           | 91.7981           | 2.1342           | 89.5745          | 0.4284      | 91.2323     |
| 2006 | 92.8     | 96.0402             | 3.4916              | 95.3867          | 2.7874           | 92.3295           | 0.5070           | 90.3447          | 3.0045      | 92.0701     |
| 2007 | 96.4     | 95.9279             | -0.4897             | 95.5584          | -0.8731          | 92.8640           | 3.6680           | 91.0559          | 5.8360      | 91.7127     |
| 2008 | 96.2     | 95.5373             | -0.6888             | 95.4540          | -0.7755          | 93.4017           | 2.9089           | 91.7127          | 4.6645      | 93.7280     |
| 2009 | 92.9     | 94.9256             | 2.1804              | 95.1278          | 2.3981           | 93.9424           | -1.1200          | 92.3193          | 0.6251      | 94.1807     |
| 2010 | 93.3     | 94.1363             | 0.8964              | 94.6212          | 1.4161           | 94.4862           | -1.2714          | 92.8795          | 0.4507      | 94.5987     |
| 2011 | 94.9     | 93.2032             | -1.7880             | 93.9663          | -0.9838          | 95.0332           | -0.1404          | 93.3968          | 1.5840      | 94.9847     |
| 2012 | 96.4     | 92.1533             | -4.4053             | 93.8839          | -3.3100          | 95.5834           | 0.8471           | 93.8746          | -2.6198     | 95.3412     |
| 2013 | 93.8     | 91.0081             | -2.9756             | 92.3096          | -1.5889          | 96.1367           | -2.4912          | 94.3158          | 0.5499      | 95.6704     |
| 2014 | 95.9     | 97.8565             | 0.3191              | 91.3456          | 2.0621           | 96.6933           | -8.6372          | 94.7232          | 5.8360      | 95.9744     |
| 2015 | 88.5     | 88.5004             | 0.0040              | 90.3111          | 2.0464           | 90.9973           | -3.9894          | 95.0495          | 7.4571      | 96.2551     |
| 2016 | 89.1     | 87.1648             | -2.1720             | 89.2179          | 0.1323           | 97.8160           | -9.7823          | 95.4470          | 7.1325      | 96.5143     |
| 2017 | 85.8     | 85.7891             | -0.0127             | 88.0761          | 2.6528           | 98.3823           | -14.6467         | 95.7680          | 11.6177     | 96.7538     |
| 2018 | 82.8     | 84.3822             | 1.9108              | 86.8944          | 4.9449           | 98.9519           | -19.5071         | 96.0643          | 16.0197     | 96.9748     |

MAPEFIT (%) = 0.8830
MAPEPRE (%) = 2.3677

MAPEFIT (%) = 3.1216
MAPEPRE (%) = 7.2953
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
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 MAPEFIT 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 MAPEFIT 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 MAPEPRE 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 comparison of seven models 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 NNGM(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 (l,l) APE (%) | NGBM (l,l) APE (%) | GM (l,l) APE (%) | NGM (l,l) APE (%) | TDGM (l,l) APE (%) | Verhulst APE (%) | AR–GM (l,l) APE (%) | MAPEFIT (%) | MAPEPRE (%) |
|------|----------|----------------------|---------------------|------------------|-------------------|-------------------|------------------|-------------------|------------|-------------|
| 2008 | 208.2061 | 208.2 | 208.2 | 0 | 208.2061 | 0 | 208.2061 | 0 | 208.2061 | 0 | 208.2 | 0 | 208.2061 | 0 |
| 2009 | 211.2094 | 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 | 218.3389 | 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 | 214.8901 | 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 | 215.0810 | 216.9167 | 1.0325 | 219.1857 | −2.1125 | 211.4598 | −1.4868 | 219.0000 | 2.0260 | 207.317 | −3.4387 | 215.3406 | 0.3212 |
|      |          |          |          |          |          | 1.7113 |          |          | 1.9369 | 1.9043 |          |                        |
| 2014 | 204.0364 | 209.6452 | 2.7672 | 213.2665 | 4.5424 | 221.8490 | −8.301 | 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 |
|      |          |          |          |          |          | 1.9800 |          |          | 4.9797 | 18.4344 |          | 14.6117 | 68.4851 | 12.1270 |
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,
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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