An MPA-based optimized grey Bernoulli model for China’s petroleum consumption forecasting

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Abstract
The remarkable prediction of petroleum consumption is of significance for energy scheduling and economic development. Considering the uncertainty and volatility of petroleum system, this paper presents a nonlinear grey Bernoulli model with combined fractional accumulated generation operator to forecast China’s petroleum consumption and terminal consumption. The newly designed model introduces a combined fractional accumulated generation operator by incorporating the traditional fractional accumulation and conformable fractional accumulation; compared to the old accumulation, the newly optimized accumulation can enhance flexible ability to excavate the development patterns of time-series. In addition, to further improve the prediction performance of the new model, marine predation algorithm is applied to determine the optimal emerging coefficients such as fractional accumulation order. Furthermore, the proposed model is verified by a numerical example of coal consumption; and this newly established model is applied to predict China’s petroleum consumption and terminal consumption. Our tests suggest that the designed ONGBM(1,1,k,c) model outperforms the other benchmark models. Finally, we predict China’s petroleum consumption in the following years with the aid of the optimized model. According to the forecasts of this paper, some suggestions are provided for policy-makers in the relevant sectors.

Keywords Grey forecasting model · Fractional accumulated generation operator · Marine predation algorithm · Petroleum consumption

Introduction
In the modern industrial era, petroleum has become a very important energy resource and a strategic economic resource. The scarcity of petroleum and the sustainable development of petroleum industry directly affect the development process of the national economy and defense security [1]. On the one hand, China is on an accelerated path to industrialization and urbanization [2], and this fact undoubtedly accelerates petroleum consumption in the secondary and tertiary industries. Specifically, Fig. 1 shows the proportion of petroleum consumption in different sectors of China; it is seen that the proportion of petroleum consumption of the secondary and tertiary industries basically dominates the total volume of petroleum consumption; therefore, the development trend of petroleum consumption will increase fast. On the other hand, Fig. 2 shows that China’s petroleum resources are located in poor and remote areas, which increases the difficulty of petroleum exploration. This fact embodies that China’s petroleum demand will rely on foreign import to a large degree [3]. On the foundation of the above-mentioned background, accurately estimating China’s petroleum consumption can assist in formulating rational plans and reducing capital waste [4].

In this context, the research regarding petroleum consumption has been received more attention. Having reviewed
literature, these methods can be divided into three groups: the statistical models, machine learning methods, and grey forecasting models. For example, to overcome the challenge of modeling and forecasting the oil consumption with traditional methods, Turanoglu et al. [5] used the artificial neural network for unfolding the oil consumption forecasting using data for population, GDP, and import and export of Turkey in the period of 1965–2010. Dritsaki et al. [6] modeled and forecasted oil consumption in Greece using Box–Jenkins methodology during 1960–2020, and their results showed a downturn in oil consumption for the following years. Yuan et al. [7] used grey model with rolling mechanism to predict global petroleum consumption. Considering the nonlinear trend in petroleum consumption. More forecasting techniques for petroleum consumption can be seen in Table 1.

By reference with Ref. [15], there is little variation in the original data, and precise forecasts can be obtained. In addition, Ofosu-Adarkwa et al. [16] argued that it is better to focus on a time-series involving the most relevant shock when modeling a time-series sequence impacted by shocks. Taking into account data availability and volatility, this paper selects the grey modeling technique as the optimal forecasting model for accurately forecasting China’s petroleum consumption. In the past decades, grey prediction model has been widely used in various fields such as energy [17–21], environment [22], COVID-19 [23], tourism [24], automobile industry [25], and economics [26]. Due to its wide application range, a variety of derivative forms have been developed from the following aspects.

As many studies show that the traditional grey model (GM(1,1)) is suitable for processing time-series with homogeneous exponential law. To this end, Cui et al. [27] proposed a new model for predicting sequences with approximate non-homogeneous exponential law. Considering the influence of time-delay effect, Ma et al. [28] suggested time-delay polynomial grey model and applied this model in China’s natural gas consumption. Qian et al. [29] designed a new grey model with time power term. Wei et al. [30] developed a grey prediction model with polynomial term and optimized this model from the perspective of background value. Liu et al. [31] developed a combined grey model based on Refs. [29, 30]. Considering the nonlinear trend in the modeling sequence, Chen et al. [32] introduced the Bernoulli equation into GM(1,1); as a consequence, the nonlinear grey Bernoulli model (NGBM(1,1)) was proposed.

In the grey modeling procedure, the cumulative operation is applied to reduce the randomness of time-series sequence, which does achieve the purpose of accurate prediction. However, some scholars found that the prediction performance was poor when we take into account the integer-order accumulation. To address this issue, Wu et al. [33] introduced the fractional accumulated generation operator into the GM(1,1) model for enhancing the prediction performance. After that, Xie et al. [34] proposed an opposite-direction fractional grey model for forecasting China’s electricity consumption. Ma et al. [35] put forward a conformable fractional grey model and explored the relationship to the traditional fractional grey model.

Additionally, to estimate the model’s parameters, the trapezoid formula are usually used to approximate the integral in grey forecasting models. Zheng et al. [36] figured that there is an inherent error using trapezoid formula. To this end, Ma et al. [37] replaced trapezoid formula by Simpson formula to improve the accuracy of background value, and he and his colleagues demonstrated the feasibility and effectiveness of the newly designed model through a range of real cases. Şahin [38] used the integral mean value theorem to optimize the background value to reduce prediction errors. Subsequently, Liu et al. [39] further used a more complicated integral mean value theorem to enhance the prediction performance of the model.
Table 1 Recent forecasting techniques for petroleum consumption

| Category                   | Author(s)            | Model designation | Case                                                                 |
|----------------------------|----------------------|-------------------|----------------------------------------------------------------------|
| Statistical models         | Azadeh et al. [8]    | Fuzzy regression + ANOVA | Oil consumption in Canada, United States, Japan and Australia from 1990 to 2005 |
|                            | Dritsaki et al. [6]  | ARIMA             | Oil consumption in Greece during 1960–2020                         |
|                            | Alkhathlan and Javid [9] | Structural time-series technique | Total oil consumption of Saudi Arabia over the period from 1971 to 2013 |
| Machine learning methods   | Al-Fattah and Aramco [10] | Artificial intelligence GANNATS model | Crude oil demand for Saudi Arabia and China |
|                            | Turanoglu et al. [5] | ANNs              | Oil consumption in Turkey from 1965 to 2010                        |
|                            | Huang et al. [11]    | Four neutral network methods | Oil consumption demand of China                                      |
| Grey forecasting models    | Yao and Wang [12]    | LSTM network + GM (1,1) | The US West Texas Intermediate (WTI) crude oil price from January 2, 1986, to January 31, 2020 |
|                            | Lu and Tsai [13]     | EWMA + REGM(1,1)  | Annual petroleum demand in Taiwan                                    |
|                            | Yang et al. [14]     | GGNNT            | China’s oil consumption                                              |
| Current study              |                      | ONGBM(1,1,k,c)    | China’s petroleum consumption and terminal consumption from 2001 to 2018 |

Having reviewed the above literature, we know that the applicable scope, accumulated generation operator, and background value of the grey forecasting model still have defects. To address this issue, this paper develops a novel nonlinear grey Bernoulli model with combined fractional accumulation (abbreviated as ONGBM(1,1,k,c)). First, we introduce a combined fractional accumulated generation operator by incorporating the traditional fractional accumulation [33] and conformable fractional accumulation [35] into the optimized nonlinear grey Bernoulli model [38]. Second, the background-value coefficient is set as a variable for increasing the flexibility of the newly designed model. Third, the marine predation algorithm (MPA) [39] is applied to determine the optimal coefficients of the proposed model. Finally, to accurately predict China’s petroleum consumption in the following years, a case of coal consumption and two sets of China’s petroleum consumption are used for validating the effectiveness of the proposed model; after that, China’s petroleum consumption and terminal consumption in the next 5 years are forecasted by the newly designed model, and some suggestions are provided for policy-makers in the relevant sectors.

The rest of this paper can be organized as follows. “Optimized nonlinear grey Bernoulli model” describes the modeling procedure of the proposed model. “Numerical validation” conducts a numerical experiment for validating the effectiveness of the proposed model. “Application in China’s petroleum consumption” applies the novel model to predict China’s petroleum consumption and “Conclusion and research direction” concludes.

Optimized nonlinear grey Bernoulli model

Combined fractional accumulated generation operator

As many studies show, the fractional accumulation generation (FAGO) has been widely used in various grey prediction models because of its flexibility and effectiveness. To further improve the performance of FAGO, this paper proposes a combined fractional accumulated generation operator (CFAGO) by incorporating the traditional fractional accumulation [33] and conformable fractional accumulation [35]. The relevant calculation formula can be seen in Theorem 1, which is helpful in establishing the proposed model in the next subsection.

\[
X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)), \quad n \geq 4 \text{ is nonnegative time-series sequence, and the combined fractional accumulated generation operator (CFAGO) of } X^{(0)} \text{ can be given by}
\]

\[
X^{(\alpha)}(k) = \sum_{i=1}^{k} \sum_{j=1}^{i} \frac{\Gamma(r + j - i)x^{(0)}(k)}{\Gamma(j - i + 1)\Gamma(r)j^{r-\tau}},
\]

where \(k = 1, 2, \ldots, n\); \(\tau, r \in (0, 1]\), and its inverse form (namely, the inverse conformable fractional accumulated generation operator (ICFAGO) is obtained as
\( x^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r + 1)(k - i)^{1-\tau}}{\Gamma(i + 1)\Gamma(r - i + 1)} \left( x^{(\alpha)}(k - i) - x^{(\alpha)}(k - i - 1) \right). \) \( (2) \)

**Proof.** Assume that \( X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \) is nonnegative sequence; according to [33], we can obtain the fractional accumulated generation operator of \( X^{(0)} \) as \( X^{(r)} = (x^{(r)}(1), x^{(r)}(2), \ldots, x^{(r)}(n)) \), where

\[ x^{(r)}(k) = \sum_{i=1}^{k} \frac{\Gamma(r + k - i)}{\Gamma(k - i + 1)\Gamma(r)} x^{(0)}(i). \] \( (3) \)

Similarly, according to [35], we get the conformable fractional accumulated generation operator (CFAGO) as

\[ x^{(\alpha)}(k) = \sum_{i=1}^{k} \frac{x^{(r)}(k)}{i^{\tau}}, \] \( (4) \)

where \( \tau \in (0, 1) \), that is, the CFAGO of \( X^{(0)} \) is

\[ x^{(\alpha)}(k) = \sum_{i=1}^{k} \sum_{j=1}^{i} \frac{\Gamma(r + j - i)}{\Gamma(j - i + 1)\Gamma(r)} x^{(0)}(k - j + 1). \] \( (5) \)

After an inverse calculation, we get

\[ x^{(r)}(k) = k^{1-\tau} \left( x^{(\alpha)}(k) - x^{(\alpha)}(k - 1) \right). \] \( (6) \)

Based on this, we easily get the inverse fractional accumulated generation operator of \( X^{(r)} \) as

\[ x^{(-r)}(k) = \sum_{i=1}^{k} \left( \frac{k - i - r - 1}{k - i} \right) x^{(0)}(i). \] \( (7) \)

Then, Eq. (7) becomes

\[ x^{(-r)}(k) = \sum_{i=1}^{k} (-1)^i \frac{\Gamma(r + 1)x^{(0)}(k - i)}{\Gamma(i + 1)\Gamma(r - i + 1)}. \] \( (8) \)

Furthermore, we can obtain the predicted value of \( X^{(0)} \) expressed as

\[ x^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r + 1)(k - i)^{1-\tau}}{\Gamma(i + 1)\Gamma(r - i + 1)} \left( x^{(\alpha)}(k - i) - x^{(\alpha)}(k - i - 1) \right). \] \( (9) \)

This completes the proof.

By reference with [33, 35], it is easily found that both the FAGO and CAGO are special cases of the CFAGO.

### Model establishment

Inspired by Wu et al. [38], this paper presents an optimized nonlinear grey Bernoulli model by introducing the CFAGO, and the different equation of the newly-designed NGBM(1,1,k,c) model can be defined as

\[ df^{(\alpha)}(t) + a f^{(\alpha)}(t) = \left( b r^2 + ct + d \right) (f^{(\alpha)}(t))^\gamma, \] \( (10) \)

where \( a \) is the development coefficient, \( b, c, d \) are the grey qualities, and \( \gamma \) is the power index and \( \gamma \neq 1 \). Obviously, when \( \alpha = 1 \), this model is transformed into NGBM(1,1,k,c); when \( \alpha = 1, b = 0 \), this model is simplified as NGBM(1,1); when \( \alpha = 1, b = 0, \gamma = 0 \), this model is presented as NGM(1,1,k,c); and when \( \alpha = 1, \gamma = 0 \), this model is converted to GMP(1,1,2). Therefore, the proposed NGBM(1,1,k,c) model has a more flexible structure and compatibility with other grey models.

### Exact solution to ONGBM(1,1,k,c)

This section gives the exact solution to the proposed model and the predicted value of the original data sequence.

First, we multiply both sides of Eq. (2) by \( [x^{(\alpha)}(t)]^{-\gamma} \), and one gets

\[ \frac{d[x^{(\alpha)}(t)]^{-\gamma}}{dt} + a[x^{(\alpha)}(t)]^{1-\gamma} = br^2 + ct + d. \] \( (11) \)

Let \( \psi^{(\alpha)}(t) = [x^{(\alpha)}(t)]^{1-\gamma} \), Eq. (11) can be written as

\[ \frac{d[\psi^{(\alpha)}(t)]}{dt} + a\psi^{(\alpha)}(t) = br^2 + ct + d. \] \( (12) \)

Furthermore, let \( A = a(1-\gamma), B = b(1-\gamma), C = c(1-\gamma), \) and \( D = d(1-\gamma) \), Eq. (12) can be then expressed as

\[ \frac{d[\psi^{(\alpha)}(t)]}{dt} + A\psi^{(\alpha)}(t) = Br^2 + Ct + D. \] \( (13) \)

By solving Eq. (13), we obtain the time response function of the ONGBM(1,1,k,c) model expressed as

\[ x^{(\alpha)}(k) = \left\{ e^{-A(k-1)} \left[ \frac{B}{A} k^2 + \frac{AC - 2B}{A^2} k + \frac{2B - AC + A^2D}{A^3} \right] \right\}^{1-\gamma}. \] \( (14) \)
With the help of the ICFAGO, the predicted value of the original series is given as

\[
x^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)(k-i)^{1-\tau}}{\Gamma(i+1)\Gamma(r-i+1)} \left( x^{(a)}(k-i) - x^{(a)}(k-i-1) \right).
\] (15)

**Parameter estimation**

This section deduces the model’s parameters \((a, b, c \text{ and } d)\); integrating both sides of Eq. (13) over the interval \([k-1, k]\), one can write

\[
\psi^{(a)}(k) - \psi^{(a)}(k-1) + A \int_{k-1}^k \psi^{(a)}(t)dt = \frac{k^3 - (k-1)^3}{3} B + \frac{k^2 - (k-1)^2}{2} C + D.
\] (16)

Using the trapezoid formula, Eq. (16) can be converted as

\[
\psi^{(a)}(k) - \psi^{(a)}(k-1) + A \int_{k-1}^k \psi^{(a)}(t)dt = \frac{k^3 - (k-1)^3}{3} B + \frac{k^2 - (k-1)^2}{2} C + D.
\] (17)

In Eq. (17), \(z^{(a)}(k)\) is the background value at point \(k\), and \(z^{(a)}(k) = [\kappa \psi^{(a)}(k) + (1-\kappa) \psi^{(a)}(k)]\), \(\kappa \in [0, 1]\). (18)

Using the least square method, we get the parameter vector

\[
\hat{\rho} = (U^T U)^{-1} U^T I
\] (19)

where

\[
U = \begin{bmatrix}
-\psi^{(a)}(2) & \frac{2^3-1^3}{3} & \frac{2^2-1^2}{2} & 1 \\
-\psi^{(a)}(3) & \frac{3^3-2^3}{3} & \frac{3^2-2^2}{2} & 1 \\
\vdots & \vdots & \vdots & \vdots \\
-\psi^{(a)}(n) & \frac{n^3-(n-1)^3}{3} & \frac{n^2-(n-1)^2}{2} & 1 \\
\psi^{(a)}(2) - \psi^{(a)}(1) \\
\psi^{(a)}(3) - \psi^{(a)}(2) \\
\vdots \\
\psi^{(a)}(n) - \psi^{(a)}(n-1)
\end{bmatrix}, I
\]

**Optimization of hyperparameters**

As above-mentioned modeling steps, it is found that the four parameters are assumed to be known. By reference with [18, 40], we establish a simple optimization problem to obtain the optimal hyperparameters in the ONGBM(1,1,k,c) model. The objective function with constraints can be defined as follows:

\[
\min_{\alpha, \tau, x, c} \text{MAPE} = \frac{1}{n} \sum_{i=1}^{n} \frac{\hat{x}^{(a)}(k) - x^{(a)}(k)}{x^{(a)}(k)} \times 100\%
\]

\[
\text{subject to:}
\begin{align*}
\alpha, \tau & \in (0, 1), x, c & \in [0, 1], y \neq 1, \\
x^{(0)} & = (x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n)) \\
x^{(a)}(k) & = \sum_{i=1}^{k} \sum_{j=1}^{i} \Gamma(r+j-i)x^{(0)}(k) \\
x^{(a)}(k) & = \frac{1}{\Gamma(r+1)\Gamma(r)^{1-\tau}} \int \hat{x}^{(a)}(k) \\
\hat{x}^{(a)}(k) & = e^{-\hat{x}^{(a)(1)}} \left[ \frac{B}{A} k + \frac{AC-2B}{A^2} k + \frac{2B-AC+4A^2D}{A^3} \right] \frac{1}{\Gamma(r+1)\Gamma(r)^{1-\tau}} \\
x^{(0)}(k) & = \sum_{i=0}^{k-1} (-1)^i \frac{1}{\Gamma(r+1)\Gamma(r)^{1-\tau}} \hat{x}^{(a)}(k-i) - \hat{x}^{(a)}(k-i-1)
\end{align*}
\] (20)

It is difficult to solve Eq. (20) because of its nonlinear characteristics. To this end, the MPA algorithm is employed to seek the optimal values of the four hyperparameters by minimizing the mean absolute percentage error (MAPE) between the fitted and original values.

MPA divides the whole system into three optimization stages based on different speed ratios, including high speed ratio, unit speed ratio, and low speed ratio. The specified algorithm is described as follows.

**Initialization phase.** Similar to most metaheuristic algorithms, MPA randomly initializes the prey positions within the search space to initiate the optimization process. The mathematical description is as follows:

\[
X_0 = X_{min} + rand(X_{max} - X_{min}),
\] (21)

where \(X_{max}\) and \(X_{min}\) indicate the search range, and \(rand()\) is generated within the random numbers.

**Optimization phase.** At the beginning of the iteration, when the predator speed is faster than the prey speed, the mathematical description of the MPA optimization process based on the exploration strategy is as follows:

\[
\begin{align*}
\text{stepsizes}_i & = R_B \otimes (\text{Elite}_i - R_B \otimes \text{Prey}_i) \\
\text{Prey}_i & = \text{Prey}_i + P \cdot R \otimes \text{stepsizes}_i
\end{align*}
\] (22)
The computational steps for the MPA algorithm-based ONGBM(1,1,k,c) model

Fig. 3 The computational steps for the MPA algorithm-based ONGBM(1,1,k,c) model

**Algorithm 1:** MPA algorithm to search for the optimal hyperparameters $\alpha, \gamma, \tau, \kappa$

- **Input:** $X(0)$, the range of values of the parameters $\alpha, \gamma, \tau, \kappa$
- **Output:** The optimal $\alpha, \gamma, \tau, \kappa$

1. Initialize the maximum number of iterations $Max_{\text{Iter}}$ and search agent population $i = 1$.
2. **for** Iter $= 1, Iter < Max_{\text{Iter}}, Iter = Iter + 1$ **do**
   3. **for** each agents **do**
      4. **if** Iter $< \frac{1}{3} Max_{\text{Iter}}$ **then**
         5. Update prey based on Eq. (22)
      6. **if** $\frac{1}{3} Max_{\text{Iter}} < Iter < \frac{2}{3} Max_{\text{Iter}}$ **then**
         7. **for** $j = 1, 2, \cdots, \frac{2}{3} n$ **do**
            8. Update prey based on Eq. (23)
         9. **for** $j = \frac{2}{3}, \cdots, n$ **do**
            10. Update prey based on Eq. (24)
      11. **if** Iter $> \frac{2}{3} Max_{\text{Iter}}$ **then**
         12. Update prey based on Eq. (26)
   13. Compute the fitness of each agents by the objective function in Eq. (20)
   14. Apply the FAD effect based on Eqs. (27) and Eq. (28)
   15. Calculate the fitness value
   16. **return** the optimal hyperparameters $\alpha, \gamma, \tau, \kappa$

where $i = 1, 2, \ldots, n$; Iter $< \frac{1}{3} Max_{\text{Iter}}$. In Eq. (22), stepsiz$e$ is the movement step. $R_B$ is the Brownian wandering random vector with normal distribution; Elite is the elite matrix constructed from the top predators. Prey is the prey matrix with the same dimension as the elite matrix. $\otimes$ is the term-by-term multiplication operator. $P$ is equal to 0.5. $R$ is a uniform random vector within $[0, 1]$; $n$ is the population size. Iter and Max_iter are the current, and maximum, numbers of iterations, respectively.

In the middle of the iteration, when the predator and the prey have the same speed, the prey is responsible for exploitation based on the Lévy wandering strategy; the predator is responsible for exploration based on the Brownian wandering strategy, and gradually shifts from the exploration strategy to the exploitation strategy. The mathematical description of exploitation and exploration is as follows:

\[
\begin{align*}
\text{stepsize}_i &= R_L \otimes (\text{Elite}_i - R_L \otimes \text{Prey}_i) \\
\text{Prey}_i &= \text{Prey}_i + P \cdot R \otimes \text{stepsize}_i
\end{align*}
\]

where $i = 1, 2, \ldots, n$; Iter $< \frac{1}{3} Max_{\text{Iter}} < Iter < \frac{2}{3} Max_{\text{Iter}}$. In Eqs. (23) and (24), $CF$ is the random vector with Lévy distribution and

\[
CF = \left(1 - \frac{\text{Iter}}{Max_{\text{Iter}}} \right)^{\frac{2\text{Iter}}{Max_{\text{Iter}}}}
\]

is the adaptive parameter to control the movement step of the predator, and the other parameters have the same meaning as above. At the end of the iteration, when the predator speed is slower than the prey speed, the predator adopts an exploitation strategy based on Lévy wandering. The mathematical description is as follows:

\[
\begin{align*}
\text{stepsize}_i &= R_L \otimes (\text{Elite}_i - R_L \otimes \text{Prey}_i) \\
\text{Prey}_i &= \text{Prey}_i + P \cdot CF \otimes \text{stepsize}_i
\end{align*}
\]

where $i = 1, 2, \ldots, n$; Iter $\geq \frac{2}{3} Max_{\text{Iter}}$.

**FADs effect.** Fish aggregation devices (FADs) or eddy effects usually change the foraging behavior of marine predators, and this strategy enables MPA to overcome the early convergence problem and escape from local extremes in the process of finding the optimal value. Its mathematical description is as follows:

When $r \leq FADs$,

\[
\text{Prey}_i = \text{Prey}_i + C F [X_{\min} + R_L \otimes (X_{\max} - X_{\min})] \otimes U.
\]

where $i = 1, 2, \ldots, n$; Iter $\geq \frac{2}{3} Max_{\text{Iter}}$.
Table 2 Fitted and predicted values and errors (%) by the different grey models in China’s coal consumption

| Year | Raw data Value | GM(1,1) Value | APE | ONGBM(1,1) Value | APE | ONGBM(1,1,k,c) Value | APE |
|------|----------------|---------------|-----|------------------|-----|----------------------|-----|
| 2000 | 21,232.01      | 21,232.01     | 0.00| 21,232.01        | 0.00| 21,232.01            | 0.00|
| 2001 | 21,342.74      | 23,120.30     | 8.33| 21,315.46        | 0.13| 21,194.82            | 0.69|
| 2002 | 22,544.05      | 24,606.03     | 9.15| 25,732.38        | 3.25| 25,334.16            | 1.65|
| 2003 | 28,749.31      | 27,870.06     | 3.06| 27,777.16        | 3.38| 27,508.17            | 4.32|
| 2004 | 30,088.94      | 29,661.02     | 1.42| 29,822.70        | 0.88| 29,746.24            | 1.14|
| 2005 | 32,245.20      | 31,567.07     | 2.10| 31,902.62        | 1.06| 31,792.33            | 1.40|
| 2006 | 34,031.60      | 33,595.61     | 1.28| 34,038.54        | 0.02| 34,286.48            | 0.75|
| 2007 | 35,498.24      | 35,754.50     | 0.72| 36,246.07        | 2.11| 36,588.54            | 3.07|
| 2008 | 38,128.59      | 38,052.12     | 0.20| 38,537.61        | 1.07| 39,018.60            | 2.33|
| 2009 | 42,874.55      | 40,497.39     | 5.54| 40,923.73        | 4.55| 41,448.62            | 3.33|
| 2010 | 43,965.84      | 43,099.80     | 1.97| 43,413.94        | 1.26| 43,878.60            | 0.20|
| 2011 | 46,678.92      | 45,869.44     | 1.73| 46,017.17        | 1.06| 46,500.56            | 0.38|
| 2012 | 59,402.17      | 62,627.40     | 5.43| 61,029.40        | 2.74| 59,865.53            | 0.78|
| 2013 | 63,004.33      | 66,651.91     | 5.79| 64,492.38        | 2.36| 62,743.20            | 0.41|
| 2014 | 67,268.27      | 70,935.03     | 5.45| 68,130.38        | 1.28| 65,684.80            | 2.35|
| 2015 | 57,125.93      | 58,845.90     | 3.01| 57,731.93        | 1.06| 57,179.84            | 0.09|
| MAPE | 2.68           | 1.50          |     | 1.42             |     |                     |     |
| NMAPE| 2.31           | 1.37          |     | 1.29             |     |                     |     |
| RMSE | 1114.44        | 713.41        |     | 641.48           |     |                     |     |
| NRMSE| 0.03           | 0.02          |     | 0.00             |     |                     |     |

When \( r > FADs \),

\[
\text{Prey}_i = [FADs(1 - r) + r](\text{Prey}_{r1} - \text{Prey}_{r2}),
\]

(28)

where \( FADs \) are the influence probabilities, taken as 0.2. \( U \) is the binary vector. \( r \) is the random number within \([0, 1]\). \( r1 \) and \( r2 \) are the random indices of the prey matrix, respectively.

The detailed computational steps for the MPA can be seen in Fig. 3.

Evaluation criterion

In this paper, four statistical indicators \([41]\) are used to evaluate the effectiveness of the model, including the mean absolute percentage error (MAPE), normalized mean absolute percentage error (NMAPE), root-mean-square error (RMSE) and normalized root-mean-square error (NRMSE). And the relevant calculation formulas can be seen as follows:

\[
\text{MAPE} = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{\tilde{x}^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right| \times 100%
\]

(29)

\[
\text{NMAPE} = \frac{1}{n} \sum_{k=1}^{n} \left| \frac{\tilde{x}^{(0)}(k) - x^{(0)}(k)}{\sum_{k=1}^{n} x^{(0)}(k)} \right| \times 100%
\]

(30)

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (\tilde{x}^{(0)}(k) - x^{(0)}(k))^2}
\]

(31)
\[
NRMS E = \sqrt{\frac{\sum_{k=1}^{n} (\hat{x}^{(0)}(k) - x^{(0)}(k))^2}{\sum_{k=1}^{n} (x^{(0)}(k))^2}},
\]

where \(x^{(0)}(k)\) and \(\hat{x}^{(0)}(k)\) are the actual value and predicted value at point \(k\), respectively.

**Numerical validation**

This section provides an example to validate the flexibility and effectiveness of the proposed ONGBM(1,1,k,c) model. The basic grey model (GM(1,1)) [42] and optimized nonlinear grey Bernoulli model (ONGBM(1,1)) [43] are selected as the benchmark models. These computational results have been computed on the software MATLAB in authors' labs.

In this section, we consider a time-series sequence from the National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/ndsj/) that describes the changing trend of China’s coal consumption. The data from 2000 to 2016 are applied to calibrate the model, while the data from 2017 to 2019 are used for examining the model’s accuracy. From Table 2, it is concluded that the proposed model is superior over other competitive models in this case.

**Application in China’s petroleum consumption**

**Data collection and experimental design**

The modeling data of petroleum consumption and petroleum terminal consumption from 2001 to 2018 are abstracted from the National Bureau of Statistics of China (http://www.stats.gov.cn/tjsj/ndsj/), as shown in Table 3.

Since China’s accession to the WTO in 2001, the Chinese economy has grown rapidly, thus leading to a dramatic increase in energy demand, and petroleum is seen as the blood of industry. Therefore, accurately forecasting China’s petroleum consumption is the motivation of this paper. To this end, this paper develops a new method for estimating the trend of China’s petroleum consumption and petroleum terminal consumption. In addition to the benchmarks mentioned in “Numerical validation”, the polynomial regression (PR) [45], artificial neural network (ANN) [46], and support vector regression (SVR) [47] are also chosen for demonstrating the effectiveness of the newly designed model.

**Experimental results**

The two datasets (annual petroleum consumption and petroleum terminal consumption) are conducted on the foundation of the mentioned competitive models, and the modeling results are listed in Tables 4, 5, 6 and 7. For visualization and intuition purposes, the forecasted values and the absolute percentage errors (APEs) generated by the six different models are graphed in Figs. 4, 5, 6 and 7. The competitive analysis will be implemented from the following angles: (1) the simulation and prediction deviations among the grey- and non-grey-based models, and (2) the effectiveness and flexibility of the proposed ONGBM(1,1,k,c) model using four calculated error-value metrics.

In Case 1, observed from Table 4 and Figs. 4 and 5, it is concluded that in the in-sample period, the intelligent methods (i.e., SVR and ANN) outperform other candidate models, because the modeling results generated by these two models are closer to the actual samples, followed by the grey models and polynomial regression. While the performance of the mentioned competitive models will be changed when it comes to the out-of-sample period. The calculated results by the proposed model are closer to the actual values and its range of APE values is narrowest among these models.

Next, we compare four different error indicators (MAPE, NMAPE, RMSE, and NRMSE). The calculated errors are tabulated in Table 5. It is obviously seen from Table 5 that the MAPE and NMAPE of the SVR model are smallest, and
## Table 4 Simulated and forecasted values of China’s petroleum consumption using different models

| Year   | Data   | GM(1,1) APE(%) | ONGBM(1,1) APE(%) | PR APE(%) | ANN APE(%) | SVR APE(%) | ONGBM(1,1,k,c) APE(%) |
|--------|--------|----------------|-------------------|-----------|------------|------------|-----------------------|
|        | Forecast value | Forecast value | Forecast value | Forecast value | Forecast value | Forecast value | Forecast value |
| Training stage | | | | | | | |
| 2001   | 22,888.40 | 22,888.40 | 0.00 | 22,888.40 | 0.00 | 22,888.40 | 0.00 |
| 2002   | 24,789.20 | 26,735.05 | 7.85 | 25,420.52 | 2.55 | 24,789.20 | 0.00 |
| 2003   | 27,125.80 | 28,336.73 | 4.46 | 27,900.26 | 2.86 | 27,125.80 | 0.00 |
| 2004   | 31,700.50 | 30,034.36 | 5.26 | 30,431.76 | 4.00 | 31,700.50 | 0.00 |
| 2005   | 32,547.00 | 31,833.70 | 2.19 | 32,746.91 | 1.75 | 32,547.00 | 0.00 |
| 2006   | 34,876.20 | 33,740.84 | 3.26 | 34,950.86 | 0.21 | 34,174.59 | 2.01 |
| 2007   | 36,658.70 | 35,762.23 | 2.45 | 36,081.83 | 3.50 | 35,407.50 | 1.72 |
| 2008   | 37,302.90 | 37,904.73 | 1.61 | 37,098.66 | 1.20 | 36,379.31 | 0.76 |
| 2009   | 38,384.50 | 40,175.57 | 4.67 | 41,346.58 | 7.72 | 40,497.16 | 5.50 |
| 2010   | 44,101.00 | 42,582.47 | 3.44 | 43,823.50 | 3.45 | 43,026.13 | 2.42 |
| 2011   | 45,378.50 | 44,294.40 | 2.45 | 45,646.68 | 0.59 | 45,151.50 | 0.50 |
| 2012   | 47,797.20 | 47,844.17 | 0.08 | 47,844.17 | 0.10 | 47,500.07 | 0.62 |
| 2013   | 49,970.60 | 50,703.40 | 1.47 | 50,083.00 | 0.23 | 49,743.66 | 0.45 |
| Testing stage | | | | | | | |
| 2014   | 51,859.40 | 53,741.00 | 3.63 | 53,158.52 | 2.51 | 50,359.65 | 2.89 |
| 2015   | 55,960.20 | 56,960.59 | 1.79 | 55,425.27 | 3.06 | 54,204.11 | 5.64 |
| 2016   | 57,692.90 | 60,373.07 | 4.65 | 56,513.30 | 2.04 | 58,990.34 | 2.25 |
| 2017   | 60,395.90 | 63,989.98 | 5.95 | 58,782.80 | 2.67 | 59,195.85 | 2.52 |
| 2018   | 62,245.10 | 67,823.58 | 8.96 | 61,058.79 | 1.91 | 64,660.15 | 3.88 |

## Table 5 Comparison of the prediction accuracies of the six models (2001–2018)

| Model            | MAPE(%) | NMAPE(%) | RMSE  | NRMSE |
|------------------|---------|----------|-------|-------|
| Training stage   |         |          |       |       |
| GM(1,1)          | 2.87    | 2.64     | 3076.17 | 0.03 |
| ONGBM(1,1)       | 1.89    | 1.86     | 1088.07 | 0.03 |
| PR               | 2.30    | 2.19     | 1043.16 | 0.03 |
| ANN              | 1.63    | 1.78     | 1019.75 | 0.03 |
| SVM              | 1.34    | 1.61     | 1624.97 | 0.04 |
| ONGBM(1,1,k,c)   | 1.71    | 1.65     | 949.66  | 0.03 |
| Testing stage    |         |          |       |       |
| GM(1,1)          | 4.99    | 5.11     | 3339.50 | 0.06 |
| ONGBM(1,1)       | 1.16    | 1.14     | 752.38  | 0.01 |
| PR               | 1.99    | 2.02     | 1291.73 | 0.02 |
| ANN              | 2.25    | 2.29     | 1518.44 | 0.03 |
| SVM              | 2.43    | 2.38     | 1692.37 | 0.03 |
| ONGBM(1,1,k,c)   | 0.91    | 0.89     | 611.14  | 0.01 |

The optimum values of the above metrics for two cases are in bold type.
### Table 6  Simulated and forecasted values of China’s petroleum terminal consumption using different models

| Year    | Data     | GM(1,1) | ONGBM(1,1) | PR     | ANN    | SVR    | ONGBM(1,1,k,c) |
|---------|----------|---------|------------|--------|--------|--------|----------------|
|         |          | Forecast value | APE(%) | Forecast value | APE(%) | Forecast value | APE(%) | Forecast value | APE(%) | Forecast value | APE(%) |
| Training stage |          |          |          |        |        |        |              |
| 2001    | 22,888.40 | 22,888.40 | 0.00    | 23,248.20 | 1.57   | 22,888.40 | 0.00    | 23,074.80 | 1.25   | 22,888.40 | 0.00 |
| 2002    | 24,789.20 | 26,735.05 | 7.85    | 24,900.39 | 0.45   | 25,420.52 | 2.55   | 24,789.20 | 0.00    | 24,789.20 | 0.00 |
| 2003    | 27,125.80 | 28,336.73 | 4.46    | 27,900.26 | 2.86   | 27,599.32 | 1.75   | 27,125.80 | 0.00    | 27,125.80 | 1.75 |
| 2004    | 31,700.50 | 30,034.36 | 5.26    | 30,431.76 | 4.00   | 29,784.60 | 6.04   | 31,700.50 | 0.00    | 31,700.50 | 0.00 |
| 2005    | 32,547.00 | 31,833.70 | 2.19    | 32,746.91 | 0.61   | 31,976.36 | 1.75   | 32,547.00 | 0.00    | 32,547.00 | 0.00 |
| 2006    | 34,876.20 | 33,740.84 | 3.26    | 34,950.86 | 0.21   | 34,174.59 | 2.01   | 33,704.23 | 3.36    | 35,051.04 | 0.50 |
| 2007    | 36,658.70 | 35,762.23 | 2.45    | 37,098.66 | 1.20   | 36,379.31 | 0.76   | 36,028.68 | 1.72    | 36,517.36 | 0.39 |
| 2008    | 37,302.90 | 37,904.73 | 1.61    | 39,223.32 | 5.15   | 38,590.50 | 3.45   | 38,608.23 | 3.50    | 38,564.13 | 3.38 |
| 2009    | 38,384.50 | 40,175.57 | 4.67    | 41,346.58 | 7.72   | 40,808.18 | 6.31   | 40,497.16 | 5.50    | 40,668.96 | 5.95 |
| 2010    | 44,101.00 | 42,582.47 | 3.44    | 43,483.85 | 1.40   | 43,032.33 | 2.42   | 41,798.22 | 5.22    | 40,668.96 | 5.95 |
| 2011    | 45,378.50 | 45,133.56 | 0.54    | 45,646.68 | 0.59   | 45,262.96 | 0.25   | 45,151.50 | 0.50    | 45,321.46 | 0.13 |
| 2012    | 47,797.30 | 47,844.17 | 0.08    | 47,844.17 | 0.10   | 47,500.07 | 0.62   | 48,048.54 | 0.53    | 47,782.52 | 0.03 |
| 2013    | 49,970.60 | 50,703.40 | 1.47    | 50,083.80 | 0.23   | 49,743.66 | 0.45   | 50,378.39 | 0.82    | 50,277.75 | 0.61 |
| Testing stage |          |          |          |        |        |        |              |
| 2014    | 51,859.40 | 53,741.00 | 3.63    | 52,371.93 | 0.99   | 51,993.73 | 0.26   | 53,158.52 | 2.51    | 50,359.65 | 2.89 |
| 2015    | 55,960.20 | 56,960.59 | 1.79    | 54,714.16 | 2.23   | 54,250.27 | 3.06   | 55,093.91 | 1.00    | 52,804.11 | 5.64 |
| 2016    | 57,692.90 | 60,373.07  | 4.65    | 57,115.53 | 1.00   | 56,513.30 | 2.04   | 58,990.34 | 2.25    | 57,433.48 | 0.45 |
| 2017    | 60,395.90 | 63,989.98 | 5.95    | 59,580.69 | 1.35   | 58,782.80 | 2.67   | 61,919.58 | 2.52    | 59,137.13 | 2.08 |
| 2018    | 62,245.10 | 67,823.58 | 8.96    | 62,114.02 | 0.21   | 61,058.79 | 1.91   | 64,660.15 | 3.88    | 62,962.36 | 1.15 |

### Table 7  Comparison of the prediction accuracies of the six models in China’s petroleum terminal consumption

|                  | MAPE(%) | NMAPE(%) | RMSE   | NRMSE  |
|------------------|---------|----------|--------|--------|
| **Training stage** |         |          |        |        |
| GM(1,1)          | 2.84    | 2.10     | 1027.63| 0.03   |
| ONGBM(1,1)       | 2.36    | 1.76     | 1127.25| 0.03   |
| PR               | 2.12    | 1.58     | 826.00 | 0.02   |
| ANN              | 2.75    | 2.08     | 1057.03| 0.03   |
| SVR              | 5.88    | 4.13     | 2227.24| 0.06   |
| ONGBM(1,1,k,c)   | **1.58**| **1.18** | **851.53**| **0.02**|
| **Testing stage** |         |          |        |        |
| GM(1,1)          | 7.93    | 7.71     | 4967.93| 0.09   |
| ONGBM(1,1)       | 3.01    | 2.91     | 1764.76| 0.03   |
| PR               | 7.64    | 7.46     | 5062.82| 0.09   |
| ANN              | 4.38    | 4.23     | 2561.14| 0.05   |
| SVR              | 2.51    | 2.33     | 2034.48| 0.04   |
| ONGBM(1,1,k,c)   | **0.71**| **0.68** | **446.85**| **0.01**|

The optimum values of the above metrics for two cases are in bold type.
RMSE and NRMSE of the ONGBM(1,1,k,c) model are lowest. On the contrary, the four error indicators of the newly proposed ONGBM(1,1,k,c) model are all lowest, and they are 0.91%, 0.89%, 611.14, and 0.01, respectively, in the test set. The newly designed model shows a higher accuracy with respect to forecasting China’s petroleum consumption.

In case 2, we conduct the two-step analysis similar to Case 1. It is seen from Table 6 and Fig. 6 that our calculated results are closer to the actual observations of China’s petroleum terminal consumption for both the training and test sets, and the newly designed model has a narrower changing range for APE values (Fig. 7), indicating that the performance stability of the proposed model is superior over other benchmarks.

Considering the four different error indices in Case 2, it is known from Table 7 that the newly designed ONGBM(1,1,k,c) model is more accurate, because its MAPE, NMAPE, RMSE, and NRMSE values are lowest for both the in-sample and out-of-sample periods. In particular, the competitors mentioned in this paper perform well in this case by reference with the Lewis standard [47]. Through the in-depth analysis, the GM(1,1) model and PR has comparatively poor forecasting abilities. And when GM(1,1) is
Fig. 6 Comparison of forecasted and actual values in China’s petroleum terminal consumption

Fig. 7 APE(%) of the six different models in China’s petroleum terminal consumption

Out-of-sample predictions and suggestion

Our tests suggest that the newly designed ONGBM(1,1,k,c) model is more suitable for forecasting China’s petroleum consumption and terminal consumption than the competitive models. Therefore, the proposed model is selected as the optimal model for making out-of-sample predictions of China’s petroleum consumption and terminal consumption in the next 5 years, and the calculated results are listed in Table 8.
According to the historical data and forecast data of petroleum consumption mentioned above, China’s petroleum consumption presents a trend of continuous growth. However, it can be seen from Fig. 2 that it is very difficult to carry out the exploration work of the petroleum in China, sustaining China’s petroleum exports at a very low level. Therefore, the supply–demand relationship of China’s petroleum will become more and more unbalanced. To avoid the contradiction between supply and demand affecting social development and national defense security, some suggestions and countermeasures for the development of China’s petroleum industry are gained as follows.

1. At present, the growth rate of China’s petroleum production is much lower than the growth rate of petroleum demand, and in recent years, petroleum production has shown a downward trend. This situation is unbelievable, because China has very large petroleum reserves. The problem that causes the unbalance of petroleum supply and demand mainly lies in the intensity of petroleum exploration. According to Fig. 2, the main reason for the difficulty in petroleum exploration is the uneven geographical distribution of China’s petroleum resources. Abundant petroleum resources are mostly stored in inaccessible places such as the Great Northwest and Northeast, where exploitation costs and difficulties are too great. Therefore, the petroleum industry should increase investment in petroleum exploitation and increase exploration and development efforts. At the same time, it is necessary to increase the input of logistics facilities and equipment, carry out crude petroleum pipeline transportation plans, and reduce the cost of crude petroleum transportation.

2. Figure 1 shows that the petroleum consumption of transportation, storage, and postal services has surpassed that of industry and has become the first industry in terms of petroleum consumption. Therefore, in the field of transportation, which belongs to the tertiary industry, the purchase of small-displacement cars can be encouraged; in the aspect of car design, energy-saving technology can be further studied to achieve the goal of energy-saving and emission reduction. In addition, related supporting facilities of new energy vehicles should be further improved, such as reasonable layout of charging piles, distribution stations, maintenance points, and other infrastructure, so as to solve the problem that cars cannot meet long-distance driving due to insufficient electric capacity. In addition, petroleum consumption in industry is second only to that of transportation, warehousing, and postal services. Therefore, China should adjust and upgrade its industrial structure, devote itself to developing high-tech and high value-added industries, and abandon the development of industries with high energy consumption.

3. By reference with the forecast results in the previous section, we can see that China’s overall petroleum consumption shows an increasing trend, while petroleum exploration will not play its due role immediately. Until China can quickly explore for petroleum, its main source of petroleum is still import. Therefore, China’s energy sector can reasonably import petroleum according to the forecast results of this paper, so as to avoid unnecessary waste caused by the excessive import of petroleum. In addition, the Chinese government can also sign agreements with major petroleum-exporting countries to continue imports, so that exporting countries can give certain discounts.

### Conclusion and research direction

To accurately predict China’s petroleum consumption, this paper proposes a newly optimized nonlinear grey Bernoulli model with combined fractional accumulated generation operator, and these varying parameters are optimized by marine predators algorithm for precisely excavating the development patterns of various time-series sequence. Specifically, we introduce a new combined conformable fractional accumulated generation operator into the existing modified nonlinear grey Bernoulli model. When we take the different values of the emerging coefficients (the fractional accumulation orders, background-value coefficient, and power index), the proposed model can be suitable for forecasting various time-series sequence issues.

As the numerical results in a series of cases show that the newly designed ONGBM(1,1,k,c) model does reach a higher accuracy in forecasting China’s coal consumption and petroleum consumption, compared with other competitive models that embrace the traditional grey model, optimized nonlinear grey Bernoulli model, polynomial regression, artificial neural network, and support vector regression. Our tests suggest that the newly proposed model should be considered the optimal technique for forecasting China’s petroleum consumption and terminal consumption in the next period. Based

### Table 8

Forecast results of China’s petroleum consumption and terminal consumption from 2019 to 2023 (10⁴ tons)

| Year | Petroleum consumption | Terminal consumption |
|------|-----------------------|----------------------|
| 2019 | 64,704.31             | 60,820.74            |
| 2020 | 66,999.01             | 62,916.77            |
| 2021 | 69,279.32             | 64,993.39            |
| 2022 | 71,548.23             | 67,053.98            |
| 2023 | 73,808.16             | 69,101.31            |

### Conclusions

The chapter concludes with a detailed analysis of the findings, highlighting the significance of the new model and its potential applications in various industrial sectors. It discusses the implications of the results for future research and policy making in the petroleum industry.
on the forecasts of this paper, some suggestions are recommended for the relevant sectors in formulating reasonable plans and strategies.

Up to this point, the newly optimized nonlinear grey Bernoulli model with combined conformable fractional accumulation has prominent advantages over the other benchmarks, whereas there remains room for improvement. For example, the proposed model is essentially a single variable-based model, neglecting relevant influential factors in practice. Additionally, other latest algorithms should be employed for improving the effectiveness of the proposed model in our next work.

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References

1. Hensel ND (2012) An economic and national security perspective on critical resources in the energy sector. In: New security frontiers: critical energy and the resource challenge, p. 113–138.
2. Wang Q, Su M, Li R (2018) Toward to economic growth without emission growth: the role of urbanization and industrialization in China and India. J Clean Prod 205:499–511
3. Zhang Z (2011) China’s energy security, the Malacca dilemma and responses. Energy Policy 39(12):7612–7615
4. Wang Q, Li S, Li R (2018) China’s dependency on foreign oil will exceed 80% by 2030: developing a novel NMG-ARIMA to forecast China’s foreign oil dependence from two dimensions. Energy 163:151–167
5. Turanoglu E, Senvar O, Kahraman C (2012) Oil consumption forecasting in Turkey using artificial neural network. Int J Energy Optim Eng (IJEOE) 1(4):89–105
6. Dritsaki C, Niklis T, Stamatiou P (2021) Oil consumption forecasting using ARIMA models: an empirical study for Greece. Int J Energy Econ Policy 11(4):214
7. Yuan C, Zhu Y, Chen D, Liu S, Fang Z (2017) Using the GM (1, 1) model to forecast global oil consumption. Grey Syst Theory Appl 7(2):286–296
8. Azadeh A, Khakestani M, Saberi M (2009) A flexible fuzzy regression algorithm for forecasting oil consumption estimation. Energy Policy 37(12):5567–5579
9. Alkhathlan K, Javid M (2015) Carbon emissions and oil consumption in Saudi Arabia. Renew Sustain Energy Rev 48:105–111
10. Al-Fattah SM, Aramo S (2021) Application of the artificial intelligence GANNATS model in forecasting crude oil demand for Saudi Arabia and China. J Petrol Sci Eng 200:108368
11. Huang Y, Li S, Wang R, Zhao Z, Huang B, Wei B, Zhu G (2021) Forecasting oil demand with the development of comprehensive tourism. Chem Technol Fuels Oils 57(2):299–310
12. Yao T, Wang Z (2020) Crude oil price prediction based on LSTM network and GM (1, 1) model. Grey Syst Theory Appl 11(1):80–94
13. Lu SL, Tsai CF (2016) Petroleum demand forecasting for Taiwan using modified fuzzy-grey algorithms. Expert Syst 33(1):60–69
14. Yang Y, Chen Y, Shi J, Liu M, Li C, Li L (2016) An improved grey neural network forecasting method based on genetic algorithm for oil consumption of China. J Renew Sustain Energy 8(2):024104
15. Hyndman RJ, Kostenko AV (2007) Minimum sample size requirements for seasonal forecasting models. Foresight 6(Spring):12–15
16. Ofosu-Adarkwa J, Xie N, Javed SA (2020) Forecasting CO2 emissions of China’s cement industry using a hybrid Verhulst-GM (1, N) model and emissions’ technical conversion. Renew Sustain Energy Rev 130:109945
17. Liu C, Wu WZ, Xie W, Zhang J (2020) Application of a novel fractional grey prediction model with time power term to predict the electricity consumption of India and China. Chaos Solitons Fractals 141:110429
18. Ding S, Li R, Wu S, Zhou W (2021) Application of a novel structure-adaptive grey model with adjustable time power item for nuclear energy consumption forecasting. Appl Energy 298:117114
19. Zeng B, Ma X, Zhou M (2020) A new-structure grey Verhulst model for China’s tight gas production forecasting. Appl Soft Comput 96:106600
20. Ma X, Mei X, Wu W, Wu X, Zeng B (2019) A novel fractional time delayed grey model with Grey Wolf Optimizer and its applications in forecasting the natural gas and coal consumption in Chongqing China. Energy 178:487–507
21. Liu C, Lao T, Wu W, Xie W, Zhu H (2022) An optimized nonlinear grey Bernoulli prediction model and its application in natural gas production. Expert Syst Appl 194:116448.
22. Javed SA, Zhu B, Liu S (2020) Forecast of biofuel production and consumption in top CO2 emitting countries using a novel grey model. J Clean Prod 276:123997
23. Şahin U, Şahin T (2020) Forecasting the cumulative number of confirmed cases of COVID-19 in Italy, UK and USA using fractional nonlinear grey Bernoulli model. Chaos Solitons Fractals 138:109948
24. Yoga I, Yudiarta IGA (2021) Grey forecasting of inbound tourism to Bali and financial losses from the COVID-19. Int J Grey Syst 1(1):48–57
25. Arsy FA (2021) Demand forecasting of toyota avanza cars in Indonesia: grey systems approach. Int J Grey Syst 1(3):38–47
26. Septyari FM (2021) Grey forecasting of the exports of Indonesian palm oil to India. Int J Grey Syst 1(2):60–68
27. Cui J, Liu SF, Zeng B, Xie NM (2013) A novel grey forecasting model and its optimization. Appl Math Model 37(6):4399–4406
28. Ma X, Liu Z (2017) Application of a novel time-delayed polynomial grey model to predict the natural gas consumption in China. J Comput Appl Math 324:17–24
29. Qian WY, Dang YG, Liu SF (2012) Grey GM (1, 1, tα) model with time power and its application. Syst Eng Theory Pract 32(10):2247–2252
30. Wei B, Xie N, Hu A (2018) Optimal solution for novel grey polynomial prediction model. Appl Math Model 62:717–727
31. Liu C, Xie W, Wu WZ, Zhu H (2021) Predicting Chinese total retail sales of consumer goods by employing an extended discrete grey polynomial model. Eng Appl Artif Intell 102:104261
32. Chen CI (2008) Application of the novel nonlinear grey Bernoulli model for forecasting unemployment rate. Chaos Solitons Fractals 37(1):278–287
33. Wu L, Liu S, Yao L, Yan S, Liu D (2013) Grey system model with the fractional order accumulation. Commun Nonlinear Sci Numer Simul 18(7):1775–1785
34. Xie W, Wu WZ, Liu C, Zhao J (2020) Forecasting annual electricity consumption in China by employing a conformable fractional grey model in opposite direction. Energy 202:117682
35. Ma X, Wu W, Zeng B, Wang Y, Wu X (2020) The conformable fractional grey system model. ISA Trans 96:255–271
36. Şahin U (2021) Future of renewable energy consumption in France, Germany, Italy, Spain, Turkey and UK by 2030 using optimized fractional nonlinear grey Bernoulli model. Sustain Prod Consum 25:1–14
37. Liu C, Lao T, Wu WZ, Xie W (2021) Application of optimized fractional grey model-based variable background value to predict electricity consumption. Fractals 29(02):2150038
38. Wu W, Ma X, Zeng B, Lv W, Wang Y, Li W (2020) A novel Grey Bernoulli model for short-term natural gas consumption forecasting. Appl Math Model 84:393–404
39. Faramarzi A, Heidarinejad M, Mirjalili S, Gandomi AH (2020) Marine predators algorithm: a nature-inspired metaheuristic. Expert Syst Appl 152:113377
40. Zeng B, Duan H, Zhou Y (2019) A new multivariable grey prediction model with structure compatibility. Appl Math Model 75:385–397
41. Candra CS, Adrian J, Lim VC (2021) Indonesian trade deficit with China: background and grey forecasting. Int J Grey Syst 1(2):33–46
42. Deng J (1982) System and control letter. Control Probl Grey Syst 1(5):288–294
43. Wang ZX, Hipel KW, Wang Q, He SW (2011) An optimized NGBM (1, 1) model for forecasting the qualified discharge rate of industrial wastewater in China. Appl Math Model 35(12):5524–5532
44. Ostertagová E (2012) Modelling using polynomial regression. Proc Eng 48:500–506
45. Sinha SK, Wang MC (2008) Artificial neural network prediction models for soil compaction and permeability. Geotech Geol Eng 26(1):47–64
46. Smola AJ, Schölkopf B (2004) A tutorial on support vector regression. Stat Comput 14(3):199–222
47. Lewis CD (1982) Industrial and business forecasting methods: a practical guide to exponential smoothing and curve fitting. Butterworth-Heinemann, Oxford

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