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China Total Energy Consumption Forecast with Optimized Continuous Conformable Fractional Grey Model

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Abstract

One of the methods used for forecasting of the time series is the fractional grey modeling approach. In this paper, the OCCFGM(1,1) model is utilized to forecasting of the total energy consumption data of China. The optimal values of α and r, which are fractional parameters in the model, are calculated using the Brute Force algorithm. Data collected from official sources from 2013 to 2022 are used to build the forecasting model, while data from 2013 to 2020 are employed to evaluate the accuracy at the model. The obtained results indicate that the OCCFGM(1,1) model exhibits superior forecasting performance compared to the other models under consideration.

Keywords Conformable fractional calculus, Energy consumption, Fractional grey model, OCCFGM(1,1) Model, Brute Force, Least squares method

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1. Introduction

The grey modeling approach is one of the sub topics of the grey system theory, firstly proposed by Deng (1982). According to this theory, it focuses on systems coping with uncertainty by representing information as known, unknown, and partially known terms. The system's information is expressed respectively as white, black, and grey, representing known, unknown, and partially known terms. Here, the term 'partially known' denotes a limited amount of information about the investigated problem. Grey prediction models have recently gained notable attention due to their utility in dealing with indeterminate or irregular systems, particularly with small sample sizes or restricted datasets.

If the raw data series is non-negative and monoton, the standard grey model can make accurate predictions (Wu et al., 2013). However, in the case of irregular time series, the standard grey model (GM(1,1)) may prove inadequate. Significant research has been conducted in recent times on grey modeling. Luo et al. (2020) proposed the constant coefficient grey Riccati model, CCRGM(1,1), by enhancing the grey Verhulst model. Wei et al. (2018) proposed another polynomial grey model. An application of three grey models for short-term load forecasting given by Özcan (2017). The EXGM(1, 1) model is formulated by Bilgil (2021) by adding an exponential term to the whitening equation of the standard grey model. Ding et al. (2022) proposed an optimized structure-adaptive grey model.

The raw data series can not be accurately analyzed by an accumulative generation operator in cases where the data is irregular. Therefore, fractional accumulation operators and fractional derivative definitions are included in the grey model to provide more suitable models for predicting irregular data (Yuxiao et al., 2020).

Wu et al. (2013) developed the GM(1,1) model with the fractional-order accumulation operator. Yuxiao et al. (2021) created a variable-order fractional grey model. Gao et al. (2022) proposed a new method based on Gompertz's law and the fractional grey model. Liu et al. (2021) suggested a novel fractional grey model.

Khalil et al. (2014) introduced a novel fractional derivative as conformable fractional derivative. The structure of this new fractional derivative definition is considered more practical than other popular fractional derivatives such as Caputo and Riemann-Liouville derivatives. Ma et al. (2020) defined conformable fractional accumulation and conformable fractional difference, and proposed a conformable fractional grey model based on these definitions. Xie et al. (2020) suggested a continuous conformable fractional grey model. W. Wu et al. (2022) proposed a conformable fractional discrete grey model, briefly denoted as CFDGM(1,1). W.-Z. Wu et al. (2022) developed a new time power-based grey model with conformable fractional derivative (CFGM($\phi, 1, t^{\alpha}$)). Erdinc et al. (2024) developed a novel fractional forecasting model by introducing an exponential grey action quantity into the whitening equation of the conformable fractional grey model.

In this article, the optimized continuous conformable fractional grey model, briefly denoted as OCCFGM(1,1) and developed by Öztürk et al. (2022), is used to predict the total energy consumption of China. By comparing prediction errors with other grey models found in the literature, it is demonstrated that the OCCFGM(1,1) model exhibited significantly lower prediction errors. Forecasts for the upcoming years are made based on the data considered in the study.

The first section provided a literature review. The second section discussed fundamental definitions and theorems. The third section introduced the OCCFGM(1,1) model. The fourth section presented the application of the model. The final section included the obtained results.

2. Conformable Fractional Calculus: Some Definitions and Properties

In this section, the definition and properties of conformable fractional derivative are given. Additionally, definitions of conformable fractional accumulation and conformable fractional difference are given (Ma et al., 2020).

Definition 1. *(See (Khalil et al., 2014))* $f:[0,\infty)\rightarrow R$ *be a differentiable function and then the conformable fractional derivative of* f *with* $\alpha\in(n,n+1]$ *order is defined as*

$$T_{\alpha}(f)(t)=\lim_{\epsilon\rightarrow 0}\frac{f\left(t+\epsilon t^{\lceil\alpha\rceil-\alpha}\right)-f(t)}{\epsilon}=t^{\lceil\alpha\rceil-\alpha}\frac{df(t)}{dt}, \tag{1}$$

where $\lceil.\rceil$ *is the ceil function, i. e. the* $\lceil\alpha\rceil$ *is the smallest integer no larger than* α. *It is clear that* $\lceil\alpha\rceil=1$ *for* $\alpha\in(0,1]$. *Thence, Equation (2.1) can be written as*

$$T_{\alpha}(f)(t)=\lim_{\epsilon\rightarrow 0}\frac{f(t+\epsilon t^{1-\alpha})-f(t)}{\epsilon}=t^{1-\alpha}\frac{df(t)}{dt},\quad \forall t>0. \tag{2}$$

Theorem 1. *(See (Khalil et al., 2014)) If the function* f *and* g *are differentiable,* $\alpha\in(0,1]$*, then we have*

1. $T_{\alpha}(f)(t)=t^{1-\alpha}\frac{df(t)}{dt}$
2. $T_{\alpha}(kf+hg)=kT_{\alpha}(f)+hT_{\alpha}(g);\forall k,h\in\mathbb{R}$
3. $T_{\alpha}(f.g)=fT_{\alpha}(g)+gT_{\alpha}(f)$
4. $T_{\alpha}\left(\frac{f}{g}\right)=\frac{gT_{\alpha}(f)-fT_{\alpha}(g)}{g^2}$
5. $T_{\alpha}(k)=0;\forall k\in\mathbb{R}$
6. $T_{\alpha}\left(t^k\right)=kt^{k-\alpha};\forall k\in\mathbb{R}$
7. $T_{\alpha}\left(e^{kx}\right)=kx^{1-\alpha}e^{kx};\forall k\in\mathbb{R}$

Definition 2. *(See (Ma et al., 2020)) The conformable fractional difference (CFD) of* f *with* α *order is defined as*

$$\Delta^{\alpha}f(k)=k^{1-\alpha}\Delta f(k)=k^{1-\alpha}[f(k)-f(k-1)] \tag{3}$$

for all $k\in N^{+}$, $\alpha\in(0,1]$ *and*

$$\Delta^{\alpha}f(k)=k^{\lceil\alpha\rceil-\alpha}\Delta^{n+1}f(k) \tag{4}$$

for all $k\in N^{+}$, $\alpha\in(n,n+1]$.

Definition 3. *(See (Ma et al., 2020)) The conformable fractional accumulation (CFA) of* f *with* α *order is defined as*

$$\nabla^{\alpha} f(k) = \nabla\left(\frac{f(k)}{k^{1-\alpha}}\right) = \sum_{j=1}^{k} \frac{f(j)}{j^{1-\alpha}} \tag{5}$$

for all $k \in N^{+}$, $\alpha \in (0,1]$ *and*

$$\nabla^{\alpha} f(k) = \nabla^{n+1}\left(\frac{f(k)}{k^{\lceil\alpha\rceil-\alpha}}\right) \tag{6}$$

for all $k \in N^{+}$, $\alpha \in (n, n+1]$.

3. The OCCFGM(1, 1) model construction

In this section, definitions and theorems about the governing differential equation of the model, the parameters of the model, the response function and the restored values are given. Then, the error analysis evaluation of the model and the Brute Force algorithm are given (Öztürk et al., 2022).

Firstly, with the time series

$$X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\right) \tag{7}$$

is given.

Conformable fractional accumulation with α order is calculated as follow,

$$X^{(\alpha)} = \left(x^{(\alpha)}(1), x^{(\alpha)}(2), ..., x^{(\alpha)}(n)\right) \tag{8}$$

where

$$x^{(\alpha)}(k) = \nabla^{\alpha} x^{(0)}(k) = \sum_{i=1}^{k} \begin{bmatrix} \lceil\alpha\rceil \\ k-i \end{bmatrix} \frac{x^{(0)}(i)}{i^{\lceil\alpha\rceil-\alpha}}, \quad \alpha \in \mathrm{R}^{+}. \tag{9}$$

In addition, $\lceil . \rceil$ is the ceil function and $\begin{bmatrix} \lceil\alpha\rceil \\ k-i \end{bmatrix} = \frac{\Gamma(k-i+\lceil\alpha\rceil)}{\Gamma(k-i+1)\Gamma(\lceil\alpha\rceil)} = \frac{(k-i+\lceil\alpha\rceil-1)!}{(k-i)!(\lceil\alpha\rceil-1)!}$ (Wu et al., 2020)

Definition 4. *(See (Öztürk et al., 2022)) The* r *−order whitening differential equation of the OCCFGM(1,1) is defined as*

$$\frac{d^{r} x^{(\alpha)}(t)}{dt^{r}} + a x^{(\alpha)}(t) = b + c e^{-t^{r}}, \tag{10}$$

where $r \in [0,1]$ *and* a *is a development coefficient,* b *is called driving coefficient and* $ce^{-t^{r}}$ *is an exponential grey action quantity. So that, the monotone decreasing term* $ce^{-t^{r}}$ *will suppress the growth of the prediction error.*

Theorem 2. *(See (Öztürk et al., 2022)) With given data and the value of fractional orders (*α *and* r*), the system parameters* a, b *and* c *of the OCCFGM(1, 1) are evaluated by using the least squares method as following,*

$$\left[\hat{a}, \hat{b}, \hat{c}\right]^{T} = \left(B^{T} B\right)^{-1} B^{T} Y, \tag{11}$$

where the matrix B, Y and $\hat{\rho}$ are

$$B = \begin{bmatrix} -0.5(x^{(\alpha)}(2) + x^{(\alpha)}(1)) & 1 & 0.5(e^{-2^r} + e^{-1^r}) \\ -0.5(x^{(\alpha)}(3) + x^{(\alpha)}(2)) & 1 & 0.5(e^{-3^r} + e^{-2^r}) \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ -0.5(x^{(\alpha)}(n) + x^{(\alpha)}(n-1)) & 1 & 0.5(e^{-n^r} + e^{-(n-1)^r}) \end{bmatrix}, Y = \begin{bmatrix} x^{(\alpha-r)}(2) \\ x^{(\alpha-r)}(3) \\ \cdot \\ \cdot \\ x^{(\alpha-r)}(n) \end{bmatrix}, \hat{\rho} = \begin{bmatrix} \hat{a} \\ \hat{b} \\ \hat{c} \end{bmatrix}. \tag{12}$$

The process of proff is omitted.

Theorem 3. *(See (Öztürk et al., 2022)) The discrete form of the response function of OCCFGM(1,1) model is given as*

$$\hat{x}^{(\alpha)}(k) = \left(x^{(0)}(1) - \frac{b}{a} - \frac{c}{a-r} e^{-1} \right) e^{\frac{a}{r}(1-k^r)} + \frac{b}{a} + \frac{c}{a-r} e^{-k^r}, \quad k = 2, 3, ..., n. \tag{13}$$

Theorem 4. *(See (Öztürk et al., 2022)) The restored values can be given as*

$$\hat{x}^{(0)}(k) = \Delta^{\alpha} \hat{x}^{(\alpha)}(k) = k^{\lceil \alpha \rceil - \alpha} \Delta^{n+1} \hat{x}^{(\alpha)}(k), \quad \alpha \in (n, n+1], k = 2, 3, ..., n. \tag{14}$$

3.1. Error Analysis of The OCCFGM(1,1) Model

Error analysis is performed using two separate assessments. At least one known data in the raw data set is separated to measure the model's prediction error. The model is employed with the remaining data, and these data used in the model is compared with the data produced by the model. Thence, the MAPE$_{fit}$ with data fitting error is calculated. Then, the MAPE$_{pre}$ is calculated for the prediction error between the reserved data or data sets and the data generated by the model. Then, the data fitting and prediction generation activities of the OCCFGM(1,1) model are separately calculated. As a result, the total Mean Absolute Percentage Error (MAPE$_{tot}$) value for these is calculated.
These are defined as follows:

$$RPE(k) = \left| \frac{\hat{x}^{(0)}(k) - x^{(0)}(k)}{x^{(0)}(k)} \right| \times 100\% \tag{15}$$

$$MAPE_{fit} = \frac{1}{p} \sum_{k=1}^{p} RPE(k) \tag{16}$$

$$MAPE_{pre} = \frac{1}{n-p} \sum_{k=p+1}^{n} RPE(k) \tag{17}$$

$$MAPE_{tot} = \frac{1}{n} (pMAPE_{fit} + (n-p)MAPE_{pre}). \tag{18}$$

Here, p represents the sample size taken from the raw data set to calculate the MAPE$_{fit}$ value, $x^{(0)}(k)$ denotes the elements of the raw data set, and $\hat{x}^{(0)}(k)$ represents the elements of the predicted data set.

3.2. Brute Force Algorithm

In this section, the utilization of the Brute Force algorithm in the model is given. The Brute Force algorithm scans the entire field, substitutes each point in the solution space into the model. The error rate is calculated for each point and the parameters with the lowest error rate are considered as optimal values.

The optimal (α, r) values are searched within a rectangular area constrained by $\alpha \in (0,1]$ and $r \in (0,1]$. Initially, α is fixed at 0, and then r is scanned over all values from 0 to 1 with a step size of $l = 0.01$. Subsequently, while keeping $\alpha = \alpha + l$ fixed, r is scanned over all values from 0 to 1 with a step size of 0.01. This process continued until the entire region is scanned. For all (α, r) points in the region, the corresponding MAPE values are calculated. Ultimately, the α and r values that yielded the minimum calculated MAPEs are determined as the optimal values.

3.3. The Posterior Variance Test

It is a statistical testing method used to evaluate the accuracy and performance of grey system theory. Developed by Deng (1996), this test is regarded as a critical tool for reducing uncertainties in forecasting models. The calculation steps of the Posterior Variance Test are as follows (Javed, 2023):

- **Step 1:** $X^{(0)} = \left(x^{(0)}(1), x^{(0)}(2), ..., x^{(0)}(n)\right)$ is given the raw data series.
- **Step 2:** $\hat{X}^{(0)} = \left(\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), ..., \hat{x}^{(0)}(n)\right)$ is given the predicted values generated by the model from the raw data series $X^{(0)}$.
- **Step 3:** The error series $\epsilon = (\epsilon(1), \epsilon(2), ..., \epsilon(n)); \epsilon(k) = x^{(0)}(k) - \hat{x}^{(0)}(k), k = 2, ..., n$ is obtained.
- **Step 4:** The root mean square deviations are calculated as follows:

$$S_1 = \sqrt{\frac{1}{n-1}\sum_{k=2}^{n}\left(x^{(0)}(k) - \overline{x}\right)^2}, \quad \overline{x} = \frac{1}{n-1}\sum_{k=2}^{n}\left(x^{(0)}(k)\right) \tag{19}$$

$$S_2 = \sqrt{\frac{1}{n-1}\sum_{k=2}^{n}(\epsilon(k) - \overline{\epsilon})^2}, \quad \overline{\epsilon} = \frac{1}{n-1}\sum_{k=2}^{n}(\epsilon(k)). \tag{20}$$

- **Step 5:** If the ratio of the root mean square deviations (S_1 and S_2) $C = \frac{S_2}{S_1} < 0.35$, then the model is significant in terms of C.
- **Step 6:** The small error probability is given by

$$P = P\{|\epsilon(k) - \overline{\epsilon}| < 0.6745 S_1\}. \tag{21}$$

  If the probability P is satisfied, then the model is considered valid in terms of P.
- **Step 7:** The small-error probability P is calculated as the ratio of the number of favourable outcomes to the total number of outcomes. Favourable outcomes are denoted as F and unfavourable outcomes as U. Here, k starts from 2 because the first value in the series generated by the model is generally the same as the first value in the raw data series. If otherwise, k should start from 1.

If the grey forecasting model is significant in terms of both C and P, the model's predictions are reliable. Otherwise, if the model is not significant for even one of them, it indicates that the model's predictions are not reliable. Table 1 presents the evaluation criteria for the Posterior Variance Test model.

Table 1. Evaluation Criteria for the Posterior Variance Test

Forecast Accuracy	P	C
Good	> 0.95	< 0.35
Qualified	0.80-0.95	0.35-0.50
Barely Qualified	0.70-0.80	0.50-0.65
Unqualified	≤ 0.7	≥ 0.65

4. Prediction of China's total energy consumption data

In this section, we estimate China's total energy consumption utilizing the OCCFGM(1,1) model. The raw data used to formulate predictions for future time periods are derived from the study conducted by the Chinese National Statistics Bureau (NBS, 2024).

The OCCFGM(1,1) model is contrasted with three fractional grey models found in the literature (CFGM(1,1), CCFGM(1,1), and ECFGM(1,1)). Firstly, the raw data is divided into two groups. The first group of data involved the creation of solution functions for the models using consumption data from 2013 to 2020, and the data fitting performance is tested. The second group of data, covering the years 2021-2022, is utilized to evaluate the models' prediction accuracy. The optimal values for α and r in the OCCFGM(1, 1) model are computed using the Brute Force algorithm, resulting in 0.6027 with a fitting error (MAPE$_{fit}$) of $\alpha = 0.95$ and $r = 0.99$. The forecasting results and prediction error rates of the models are presented in Table 2.

Table 2. Prediction and MAPE values for the total energy consumption in China utilizing four models (10000 tons of SCE).

Year	Raw Data	CFGM	CCFGM	ECFGM	OCCFGM
2013	416913	416913.00	416913.00	416913.00	416913.00
2014	428334	422440.64	423717.67	429020.00	428325.15
2015	434113	434843.58	435155.09	431454.39	432844.68
2016	441492	447083.77	447021.90	443090.48	443785.89
2017	455827	459371.94	459245.75	457424.65	457062.08
2018	471925	471805.21	471814.11	471924.48	471194.52
2019	487488	484438.50	484728.25	485781.67	485679.25
2020	498314	497307.52	497994.07	498834.16	500367.84
MAPE_{fit}		0.5551	0.4967	0.2424	**0.2528**
2021	525896	510438.02	511619.45	511132.56	515236.29
2022	541000	523850.11	525613.35	522780.59	530300.73
MAPE_{pre}		3.0546	2.7794	3.0875	**2.0023**
MAPE_{tot}		1.0550	0.9532	0.8114	**0.6027**

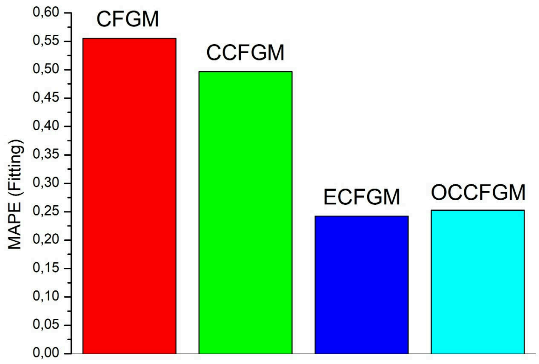

Figure 1. Fitting MAPE values of the models.

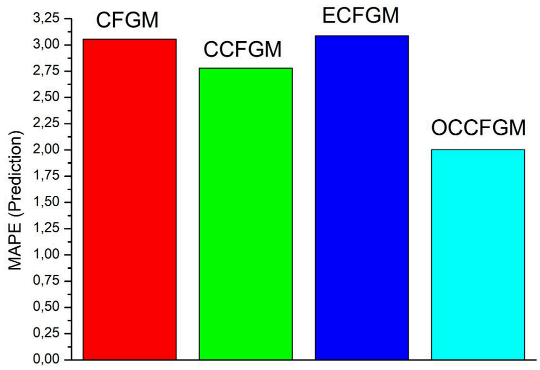

Figure 2. Prediction MAPE values of the models.

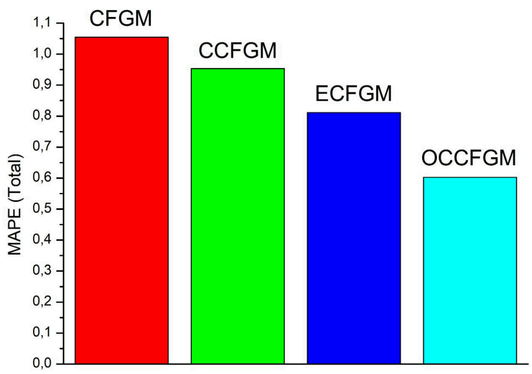

Figure 3. Total MAPE values of the models.

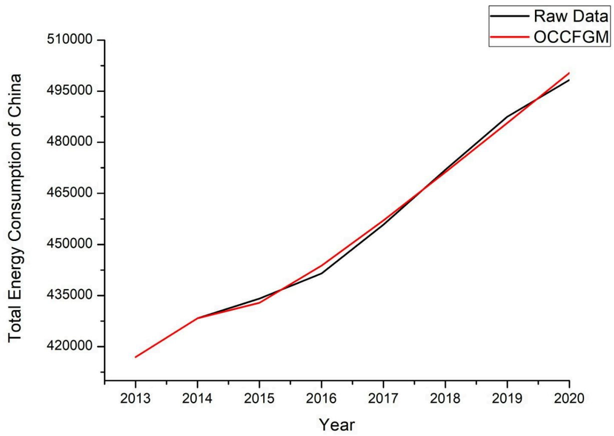

Figure 4. Real and fitting values of China's total energy consumption.

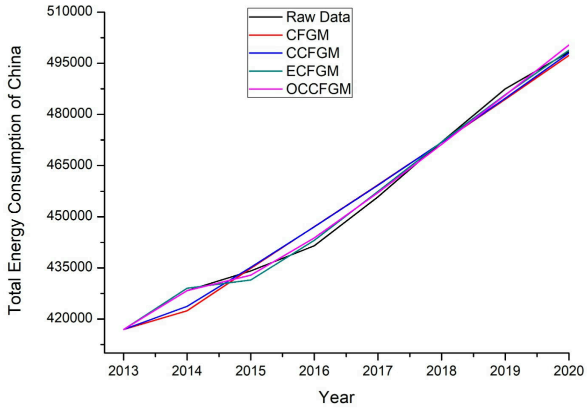

Figure 5. Simulation of real values for the total energy consumption of China using four grey models..

The results obtained according to Table 2 are as follows:

i) The MAPE$_{fit}$ values for the four distinct grey models under consideration are calculated as $\%0.5511, \%0.4967, \%0.2424,$ and $\%\mathbf{0.2528}$, respectively. In the data fitting period, the ECFGM(1, 1) model showed the best performance, while the OCCFGM(1, 1) model exhibited the second-best prediction accuracy (see Figure 1).

ii) The MAPE$_{pre}$ values for the four distinct grey models are calculated as $\%3.0546, \%2.7794, \%3.0875,$ and $\%\mathbf{2.0023}$, respectively. It can be observed that the OCCFGM(1,1) model demonstrates the most effective forecasting performance (see Figure 2).

iii) The total prediction error rates, MAPE$_{tot}$ values, for the models are calculated as $\%1.0550, \%0.9532, \%0.8114$ and $\%\mathbf{0.6027}$, respectively. Thus, it is observed that the OCCFGM(1,1) model possesses a high forecasting capability (see Figure 3).

iv) The graphical comparison of the predicted values obtained from the OCCFGM(1,1) model and the raw data series is presented in Figure 4. Additionally, the values of China's total energy consumption obtained with four different models are indicated in Figure 5.

v) The OCCFGM(1,1) model is utilized to predict China's total energy consumption values, and the forecast values for the upcoming years are given in Table 3.

Table 3. Forecasting the total energy consumption values of China (10000 tons of SCE).

Year	Forecasting values
2023	545587.61
2024	561123.93
2025	576934.47
2026	593041.45
2027	609464.88
2028	626222.99

Finally, the Posterior Variance Test is applied to evaluate the significance of the predictions made by the OCCFGM(1, 1) model. First, to examine the significance in terms of C, S_1 is calculated as 25064.75277 and S_2 as 1510.617696. Subsequently, the ratio of the root mean square deviations is given by $C = \frac{S_2}{S_1} = 0.0602$, which is less than 0.35, indicating significance in terms of C. Secondly, the necessary calculations to evaluate the significance in terms of P are provided in the sixth column of Table 4. According to the P probability, the number of favourable outcomes is 7, with a total of 7 possible outcomes, yielding $P = 1$. Since the P value is greater than 0.95, it indicates significance in terms of P. According to Table 1, it is concluded that the prediction performance of the OCCFGM(1, 1) model is reliable.

Table 4. Forecast Error Analysis for China Using the Posterior Variance Test.

Year	$\epsilon(\mathbf{k})$	$(\epsilon(\mathbf{k}) - \overline{\epsilon})^2$	$\left(\mathbf{x}(\mathbf{k}) - \mathbf{x}^{-}\right)^2$	$\lvert\epsilon(\mathbf{k}) - \overline{\epsilon}\rvert$	$\lvert\epsilon(\mathbf{k}) - \overline{\epsilon}\rvert < \mathbf{0.6745S_1}$	F or U
2014	8.85	0.6822245488$\times 10^5$	0.9801819162$\times 10^9$	261.1942857	Yes	F
2015	1268.32	0.2312419871$\times 10^7$	0.6517225448$\times 10^9$	1520.664286	Yes	F
2016	-2293.89	0.4167908902$\times 10^7$	0.3294173128$\times 10^9$	2041.545714	Yes	F
2017	-1235.08	0.9657694842$\times 10^6$	0.1455313469 10^8	982.7357143	Yes	F
2018	730.48	0.9659435766$\times 10^6$	0.1508755995$\times 10^9$	982.8242857	Yes	F
2019	1808.75	0.4248109656$\times 10^7$	0.7754076744$\times 10^9$	2061.094286	Yes	F
2020	-2053.84	0.3245386808$\times 10^7$	0.1495534636$\times 10^{10}$	1801.495714	Yes	F

5. Conclusions

In this paper, the OCCFGM(1,1) model, utilized for the purpose of forecasting China's total energy consumption, is comprehensively examined, and its performance is compared with three different fractional grey models, namely CFGM(1,1), CCFGM(1,1), and ECFGM(1,1). The data used in the study are obtained from a comprehensive survey conducted by the China National Bureau of Statistics. The results obtained are presented below:

1. **Data Analysis and Model Calibration:** The data is divided into two distinct periods for the purpose of constructing solution functions and evaluating the performance of data fitting. During the data fitting period of 2013-2020, the OCCFGM(1,1) model exhibited impressive performance, achieving a total MAPE value of $\%0.6027$ with optimal parameters $\alpha = 0.95$ and $r = 0.99$.
2. **Comparison of Results:** In the comparison conducted during the data fitting period, the OCCFGM(1,1) model exhibited the second-best prediction error rate with a $MAPE_{fit}$ value of $\%0.2528$. Throughout the predicting period (2021-2022), the OCCFGM(1,1) model emerged as the

most effective model, yielding a $MAPE_{pre}$ value of $\%2.0023$. Overall, the prediction error rates, $MAPE_{tot}$ values, indicate that the OCCFGM(1,1) model possesses the best predictive capabilities.
3. **Graphical Representation and Future Predictions:** The graphical comparison between the predicted values obtained from the OCCFGM(1,1) model and the raw data series in Figure 4, and the visual representations in Figure 5 depicting the total energy consumption values of China offered by four different models, enhanced the comprehensibility of the results.
4. **Future Projections:** The OCCFGM(1,1) model, distinguished by its prominent features, is used to forecast China's total energy consumption for future years, and these forecasted values are detailed in Table 2.

This study highlights the effective predictive capabilities of the OCCFGM(1,1) model in forecasting China's energy consumption, revealing its potential significance as a valuable tool in shaping energy policies.

Declarations

Conflict of interest The authors have no competing interests to declare that are relevant to the content of this article.

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