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Research Article

Forecasting Natural Gas Consumption of China Using a Novel Grey Model

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As is known, natural gas consumption has been acted as an extremely important role in energy market of China, and this paper is to present a novel grey model which is based on the optimized nonhomogeneous grey model (ONGM (1,1)) in order to accurately predict natural gas consumption. This study begins with proving that prediction results are independent of the first entry of original series using the product theory of determinant; on this basis, it is a reliable approach by inserting an arbitrary number in front of the first entry of original series to extract messages, which has been proved that it is an appreciable approach to increase prediction accuracy of the traditional grey model in the earlier literature. An empirical example often appeared in testing for prediction accuracy of the grey model is utilized to demonstrate the effectiveness of the proposed model; the numerical results indicate that the proposed model has a better prediction performance than other commonly used grey models. Finally, the proposed model is applied to predict China's natural gas consumption from 2019 to 2023 in order to provide some valuable information for energy sectors and related enterprises.

1. Introduction

In the past decade, China has turned into the second largest economy and third largest natural gas consumer market globally [1]. In particular, by the China Natural Gas Development Report (2019), it should be noticed that natural gas consumption of China has reached 280.3 billion cubic meters in 2018, up to 17.5% year-on-year and accounted for 7.8% of primary energy consumption. In terms of consumption structure, industrial fuel, urban gas, power generation, and chemical gas accounted for 38.6%, 33.9%, 17.3%, and 10.2%, respectively. It remarkably turned out that the former two sectors increased more, whose overall natural gas consumption accounted for 351 billion cubic meters. From the perspective of regional consumption, the consumption levels of natural gas in all provinces increased significantly. Natural gas consumption in the Beijing-Tianjin-Hebei region was 43.9 billion cubic meters that accounted for 15.6% of national natural gas consumption. The scales of four provinces, such as Zhejiang, Hebei, Henan, and Shanxi, first exceeded 10 billion cubic meters. The number of provinces where natural gas consumption exceeded 10 billion has been up to ten. Accordingly, a series of problems might be considered: How do we make reasonably distribution on reserves? How do we price this? and How much natural gas we consume? In order to answer these, one must recognize that, in making decision processes, forecasting is one of the key tools. Therefore, this paper aims to present a proper model to predict natural gas consumption of China.

2. Previous Literature Studies

2.1. Research on Forecasting Natural Gas Consumption. As mentioned in paper [2], the work on forecasting natural consumption has begun in the middle of the last century. In the

Table 1: Summary of the empirical literature in Section 2.1.

Author(s)	Model	Countries	Forecasting horizon
Hubbert [3, 4]	Hubbert curves	US	Energy from fossil fuels; nuclear energy
Brown et al. [5]	Feed-forward network	US	Gas consumption
Bartels et al. [6]	Statistical analysis	Australia	Gas consumption
Lin and Wang [8]	Logistic and Gaussian curves	China	Natural gas supply
Shaikh and Ji [9]	Logistic modelling analysis	China	Natural gas consumption
Wadud et al.[10]	Dynamic econometric model	Bangladesh	Natural gas demand
Soldo et al.[11]	Neural networks	Croatia	Residential natural gas consumption
Ervural et al.[12]	GA-based ARMA	Turkey	Natural gas consumption
Gascón and Sánchez-Úbeda [13]	Linear additive models	Simulated data	Natural gas demand
Wei et al.[14]	Hybrid model	China	Daily natural gas consumption
Özmen et al. [15]	MARS; CMARS	Turkey	Natural gas consumption
Sen et al. [16]	Multiple regression	Turkey	Natural gas consumption
Chai et al. [17]	LMDI-STIRPAT-PLSR	China	Natural gas consumption

past several decades to nowadays, numerous methods have been designed and developed to solve this issue. Nevertheless, in his paper, a systematically historic overview on forecasting techniques is given. One valuable mentioning is the Hubbert curve model [3, 4]. Significantly, he established this famous model based on mathematical relations involving fully exhaustible resources to investigate the life cycle of fossil fuel fields including natural gas. Later, this model has been regarded as the standard model to forecast natural gas consumption in the world. In addition, inevitably, some competitive prediction models have been found in our insights continuously, such as feed-forward artificial neural network [5], conditional demand analysis [6], and statistical multivariable regression [7]. In particular, in recent years, more and more methodologies have rapidly emerged to clearly offer valuable information for decision-makers in advance, due to the rapid raise in developing countries, for instance, China, India, and Korea, along with corresponding requirement on energy, especially on clear energy, including natural gas. This again causes a tremendous surge in research on this issue. For example, Lin and Wang [8] investigated natural gas supply in China that included production peak and import trends. Analogous to this way, Shaikh and Ji [9] employed logistic modelling analysis to predict natural gas demand in China. A dynamic econometric model is designed to model and forecast natural gas demand in Bangladesh [10]. Soldo et al. [11] introduced solar radiation into the residential natural gas consumption forecasting model to improve it. Considering that the mixed model had advantage over the single model, naturally, some focused on how to efficiently combine these single models. For example, Ervural et al. [12] presented a novel forecasting method that combined the autoregressive moving average method and genetic algorithm in order to accurately forecast Istanbul's natural gas consumption. More recently, Gasćon and Sánchez-Úbeda [13] proposed an automatic specification process for forecasting models under additivity assumptions, along with piecewise linear regression. A novel hybrid model was applied to predict daily natural gas consumption [14]. Summary of the empirical literature is given in Table 1.

2.2. Research on the Grey System Model. As we can see from the above description, it is clearly known that all of these models can be regarded as the statistical model and intelligent model that have been proved to work quite well with sufficient datasets. However, the fact is that it is difficult for some systems, or sometimes impossible, to offer enough data for us to model, including emerging industry and catastrophe. As such, identifying a fairly appreciable model for a small sample becomes crucial in practical applications. Obviously, Professor Deng [18], a pioneer on grey system theory, would like to solve this topic and gave an innovative theory often called the grey system theory. In particular, the grey forecasting model, a key branch of this theory, has been widely concerned and applied in many fields, including engineering, economy, and especially energy (see [19–28]). In addition, as a basic model in grey system model, which is abbreviated as GM (1,1). In the past three decades, numerously generalized and improved models based on GM (1,1) have emerged continuously, for example, GMC (1,n) [29], NGBM (1,1) [30], DGM (1,1) [31], FAGM (1,1) [32], NGM (1,1) [33], and CFGM [34]. It turns out that the grey model has an appreciable forecasting ability in energy field, which means that it would work well in forecasting natural gas consumption. Several recent evidences existed in the previous literature, for instance, Wang et al. [35] combined the multicycle Hubbert model and rolling grey model in order to analyze natural gas production and consumption in China. Ma and Liu [36] used a time-delayed polynomial grey model to predict China's natural gas consumption. The following year, Wu and Shen [37] proposed the grey-related least squares support vector machine optimization model to perform prediction on natural gas consumption. Other grey models used in predicting natural gas consumption can be seen in the study of Shaikh et al. [38] and Zeng and Li [39].

2.3. Contribution and Organization. Contribution of this paper is twofold. One contribution is that a novel grey model is proposed to increase prediction accuracy of the existing grey model, which is based on the nonhomogeneous grey model. In particular, the product of determinant is firstly used in the nonhomogeneous grey model in order to prove that the forecasting result of the existing model is independent of the first entry of the original series. This motivates a novel grey model, inserting an arbitrary number in the front of the first entry of original series to extract messages [40], to be proposed. Another contribution is that we apply this model to predict China's natural gas consumption from 2019 to 2023 after verifying effectiveness of the proposed model.

The rest of this paper is organized as follows: Section 3 depicts modelling procedure of the existing nonhomogeneous grey model. Section 4 proves that the forecasting result is being independent of the first entry of original series and presents a novel grey model for increasing prediction accuracy of the existing model. Validation of the proposed model is carried out in Section 4. Section 5 we apply the proposed model to predict China's natural gas and the conclusions are given in final section.

3. Methodology

3.1. Description of the Nonhomogeneous Grey Model. The nonhomogeneous grey model which is abbreviated as NGM (1,1) is firstly proposed by Cui, while forecasting results do not fit well with the actual data in most applications. Therefore, Zhan and Shi [41] suggested plugging a constant into the grey control parameter; as a result, a novel nonhomogeneous grey model was proposed. Afterward, Ma et al. [42] denoted this model as ONGM and its modelling steps are depicted as follows:

Suppose

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

be a nonnegative series and then the first-order accumulative generating operator series be

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

where $x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), i = 1, 2, \ldots, n$. The differential equation

$$\frac{\mathrm{d}x^{(1)}(t)}{\mathrm{d}t} + ax^{(1)}(t) = tb + c \tag{3}$$

is called the basic ONGM model. Obviously, (3) would become NGM (1, 1) when constant c equals to zero. The discrete form of (3) can be given by

$$x^{(0)}((k)) + az^{(1)}(k) = kb + c, \tag{4}$$

where $z^{(1)}(k)$ is often called the background value, and further

$$z^{(1)}(k) = 0.5\left(x^{(1)}(k-1) + x^{(1)}(k)\right). \tag{5}$$

The purpose of approximately obtaining (4) is to estimate system parameters a, b, and c by the least squares method, which is

$$(a, b, c)' = \left(B'B\right)^{-1} B'Y, \tag{6}$$

where

$$B = \begin{bmatrix} -z^{(1)}(2) & 2 & 1 \\ -z^{(1)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & n & 1 \end{bmatrix}, \quad Y = \left[x^{(0)}(2), x^{(0)}(3), \cdots, x^{(0)}(n)\right]'. \tag{7}$$

As such, the solution to (3) with $x^{(1)}(1) = x^{(0)}(1)$ can be acquired as follows:

$$\widehat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a}\right)e^{-a(k-1)} + \frac{b}{a}k - \frac{b}{a^2} + \frac{c}{a}. \tag{8}$$

The simulative values of $X^{(0)}$ and $\widehat{X}^{(0)}$ can be written as follows using the first-order inverse accumulative generating operator (IAGO):

$$\widehat{x}^{(0)}(k) = \left(1 - e^{a}\right)\left(x^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a}\right)e^{-a(k-1)} + \frac{b}{a}. \tag{9}$$

One valuable mention, as discussed in Tien, is that inserting an arbitrary number in front of the first entry to extract messages can enhance prediction accuracy and can make the model feasible in smaller samples. But we must notice that this operation is based on forecasting result independent of the first entry of original series. The following section illustrates how this question is simply answered by using the product theory of the determinant.

3.2. Study of the Relation between Forecasting Results and First Entry of the Original Series. In order to demonstrate the fact that the forecasting results of ONGM do not depend on the first entry of original series, we add the first entry by an arbitrary number δ, that is, $x^{(0)}(1) + \delta$. Furthermore, we have $X^{(1)} + \delta$. The matrix B and system parameters, respectively, become

$$H = \begin{bmatrix} -z^{(1)}(2) - \delta & 2 & 1 \\ -z^{(1)}(3) - \delta & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) - \delta & n & 1 \end{bmatrix}, \tag{10}$$

$$(u, v, w)' = \left(H'H\right)^{-1} H'Y. \tag{11}$$

In other words, the null assumption that the forecasting result is dependent of the first entry will hold if the result generated from $X^{(1)}$ equals to that generated from $X^{(1)} + \delta$. Incidentally, we introduce the product theory of the determinant briefly because we need to use this to complete the proof.

Suppose two matrices E and F with orders $p \times q$ and $q \times p$ be separately written as

$$D=\begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1q} \\ d_{21} & d_{22} & \cdots & d_{2q} \\ \cdots & & & \\ d_{p1} & d_{p2} & \cdots & d_{pq} \end{bmatrix}, \quad E=\begin{bmatrix} e_{11} & e_{12} & \cdots & e_{1p} \\ e_{21} & e_{22} & \cdots & e_{2p} \\ \cdots & & & \\ e_{q1} & e_{q2} & \cdots & e_{qp} \end{bmatrix}. \tag{12}$$

Lemma 1 (see [43]). *If* $\begin{bmatrix} D & 0 \\ -I & E \end{bmatrix}$ *and* $\begin{bmatrix} I & D \\ 0 & I \end{bmatrix}$ *are both the partitioned matrices, then the following equations hold true:*

$$\begin{bmatrix} I & D \\ 0 & I \end{bmatrix}\begin{bmatrix} D & 0 \\ -I & E \end{bmatrix}=\begin{bmatrix} 0 & DE \\ -I & E \end{bmatrix}, \tag{13}$$

$$\begin{vmatrix} D & 0 \\ -I & E \end{vmatrix}=\begin{vmatrix} 0 & DE \\ -I & E \end{vmatrix}=|DE|. \tag{14}$$

We denote that the adjoint matrix of $H'H$ by $(H'H)^*$ can be written as $(H'H)^{-1}=(1/|H'H|)(H'H)^*$. Subsequently, (5) becomes $(u,v,w)^{-1}=(1/|H'H|)(H'H)^*H'Y$. From (8)–(11), the following is easily yielded:

$$\left|H'H\right|=\begin{vmatrix} H' & 0 \\ -I & H \end{vmatrix}=\begin{vmatrix} z_2-\delta & z_3-\delta & \cdots & z_n-\delta & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ 1 & 1 & \cdots & 1 & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2-\delta & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3-\delta & 3 & 1 \\ \cdots & & & & & & \\ 0 & 0 & \cdots & -1 & z_n-\delta & n & 1 \end{vmatrix}, \tag{15}$$

where $z_i=-z^{(1)}(i), i=2,3,\ldots,n$. According to elementary row and column operations, we obtain

$$\left|H'H\right|=\left|B'B\right|. \tag{16}$$

Besides, system parameters u, v, and w are the fact rewritten as

$$u=\frac{U}{\left|H'H\right|}, \quad v=\frac{V}{\left|H'H\right|}, \quad w=\frac{W}{\left|H'H\right|}, \tag{17}$$

where $U,V,$ and W are the determinant after replacing the first, second, and third row of $|B'B|$ by Y', that is,

$$u=\frac{1}{\left|H'H\right|}\begin{vmatrix} x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ 1 & 1 & \cdots & 1 & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2-\delta & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3-\delta & 3 & 1 \\ \cdots & & & & & & \\ 0 & 0 & \cdots & -1 & z_n-\delta & n & 1 \end{vmatrix}=a,$$

$$v=\frac{1}{\left|H'H\right|}\begin{vmatrix} z_2-\delta & z_3-\delta & \cdots & z_n-\delta & 0 & 0 & 0 \\ x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) & 0 & 0 & 0 \\ 1 & 1 & \cdots & 1 & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2-\delta & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3-\delta & 3 & 1 \\ \cdots & & & & & & \\ 0 & 0 & \cdots & -1 & z_n-\delta & n & 1 \end{vmatrix}=b,$$

$$\begin{aligned} v &= \frac{1}{\left|H'H\right|}\begin{vmatrix} z_2-\delta & z_3-\delta & \cdots & z_n-\delta & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2-\delta & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3-\delta & 3 & 1 \\ \cdots & & & & & & \\ 0 & 0 & \cdots & -1 & z_n-\delta & n & 1 \end{vmatrix} \\ &= \frac{1}{\left|H'H\right|}\left(\begin{vmatrix} z_2 & z_3 & \cdots & z_n & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2 & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3 & 3 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -1 & z_n & n & 1 \end{vmatrix} - \delta\begin{vmatrix} 1 & 1 & \cdots & 1 & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2 & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3 & 3 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -1 & z_n & n & 1 \end{vmatrix}\right) \\ &= c+\delta a. \end{aligned} \tag{18}$$

From the above computation, it can be concluded that $u = a, v = b$, and $w = c + \delta a$. Therefore, forecasts results with these new parameters are

$$\begin{aligned}&(1-e^{u})\left(x^{(0)}(1)+\delta-\frac{v}{u}+\frac{v}{u^{2}}-\frac{w}{u}\right)e^{-u(k-1)}+\frac{v}{u}\\&=(1-e^{a})\left(x^{(0)}(1)+\delta-\frac{b}{a}+\frac{b}{a^{2}}-\frac{c+\delta a}{a}\right)e^{-a(k-1)}+\frac{b}{a}\\&=\widehat{x}^{(0)}(k).\end{aligned} \tag{19}$$

Hence, forecast results obtained by using $x^{(0)}(1)+\delta$ as the first entry is the same as those obtained by using $x^{(0)}(1)$ as the first entry, as is expected, which implies forecasts are independent of the first entry of original series.

3.3. Presentation of the Proposed Model. We could rebuild the nonhomogeneous grey model by inserting an arbitrary number in front of the first entry of original series when we prove forecasts are independent of the first entry of original series, as mentioned in Section 2.3. We write the proposed model as FNGM for simplicity. Modelling procedure is very analogous to ONGM but with a bit modification.

The modelling series $X^{(0)}$ becomes

$$X^{(0)}=\left\{x^{(0)}(0),x^{(0)}(1),\cdots,x^{(0)}(n)\right\}. \tag{20}$$

The matrices B and Y are constructed as

$$\begin{aligned}H&=\begin{bmatrix}-z^{(1)}(1) & 1 & 1\\ -z^{(1)}(2) & 2 & 1\\ & \cdots & \\ -z^{(1)}(n) & n & 1\end{bmatrix},\\ Y_{R}&=\left[x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\right]^{T}.\end{aligned} \tag{21}$$

Then, the model parameters can be obtained using the least squares method as

$$\begin{pmatrix}a\\ b\\ c\end{pmatrix}=\left(\mathrm{H}^{T}\mathrm{H}\right)^{-1}\mathrm{H}^{T}Y_{R}. \tag{22}$$

The time response function can be computed as

$$\widehat{x}^{(1)}(k)=\left(x^{(0)}(0)-\frac{b}{a}-\frac{c}{a}+\frac{b}{a^{2}}\right)e^{-a(k-1)}+\frac{b}{a}+\frac{c}{a}-\frac{b}{a^{2}}. \tag{23}$$

Consequently, by using the first-order inverse accumulative generating operation (1-IAGO), the restored values are acquired as

$$x^{(0)}(k)=\widehat{x}^{(1)}(k)-\widehat{x}^{(1)}(k-1). \tag{24}$$

To assess prediction accuracy of the proposed model, three statistical indices including the root mean square error (RMSE), mean absolute error (MAE), and mean absolute percentage error (MAPE) are employed to characterize forecasting accuracy of the model, which are separately defined as follows:

$$\begin{aligned}\mathrm{RMSE}&=\sqrt{\frac{1}{n-1}\sum_{i=2}^{n}\left|(e(i))^{2}\right|},\\ \mathrm{MAE}&=\frac{1}{n-1}\sum_{i=2}^{n}|e(i)|,\\ \mathrm{MAPE}&=\frac{1}{n-1}\sum_{i=2}^{n}\frac{|e(i)|}{x^{(0)}(k)}\times 100\%,\end{aligned} \tag{25}$$

where $e(i)$ is the simulated error at time i and $e(i)=\widehat{x}^{(0)}(i)-x^{(0)}(i)$.

4. Validation of FNGM

Before applying the proposed method to predict China's natural gas consumption, one must validate the effectiveness of the proposed model. In addition, the competitive models including the traditional grey model (GM (1,1)), the discrete grey model (DGM (1,1)), and the optimized grey model (ONGM) are established in this section.

We consider data from paper [44]. In this case, raw data are broken down into two groups. In other words, the former 10 points are used to build these four prediction models, and the others are used for testing their prediction accuracies.

In Table 2, it is clear to see that all statistical indices of FNGM are lower than those of the other three models either in the training or testing stage. This implies that FNGM has a better prediction performance in this case.

5. Application

5.1. Data Source. In this section, raw data of China's natural gas consumption from 2005 to 2018 are collected from the National Bureau of Statistics of China and can be downloaded from http://www.stats.gov.cn/english, as shown in Table 3. In particular, we divide these datasets into two groups, where data from 2005 to 2016 are used for building these models and the others are employed to test their forecasting ability.

5.2. Analysis of Forecasting Results. By calculation, the results of prediction performance of these models are given in Tables 4 and 5.

Ignoring the first item of simulative values, it is clearly seen from Table 4 that the minimum APE values of these models are 0.01, 0.01, 0.02, and 0.01 in the training stage and the maximum APE values are 0.17, 0.17, 0.18, and 0.18, separately. For the testing stage, the minimum APE values of these four models are 0.06, 0.06, 0.12, and 0.05 and the maximum APE values are 0.04, 0.04, 0.06, and 0.05, respectively. Though the maximum APE values of the proposed model are little higher than of other models, the other

Table 2: Fitted values and statistical indices by different grey models.

Raw data	GM (1,1)	DGM (1,1)	ONGM (1,1)	FNGM
0.155				
1.11	1.76	1.77	0.84	1.37
1.92	2.06	2.07	1.46	2.04
2.24	2.40	2.42	2.06	2.67
3.03	2.81	2.82	2.65	3.27
3.33	3.28	3.29	3.22	3.84
4.16	3.82	3.84	3.78	4.38
4.64	4.47	4.49	4.33	4.89
5.18	5.21	5.24	4.87	5.37
5.60	6.09	6.11	5.39	5.83
RMSE	0.32	0.32	0.31	0.30
MAE	0.25	0.25	0.29	0.27
MAPE	11.44	11.63	10.86	10.06
6.25	7.11	7.13	5.90	6.26
6.39	8.30	8.33	6.40	6.67
7.35	9.69	9.72	6.88	7.06
RMSE	2.95	2.99	0.46	0.02
MAE	1.70	1.73	0.28	0.19
MAPE	25.16	25.56	4.05	2.83

Table 3: Raw data on natural gas consumption of China from 2005 to 2018 (10^4 tons of SEC).

Year	Raw data
2005	6273
2006	7735
2007	9343
2008	10901
2009	11764
2010	14426
2011	17804
2012	19303
2013	22096
2014	24271
2015	25364
2016	27904
2017	31397
2018	36192

Table 4: Fitted values of raw data on China's natural gas consumption by different grey models.

Raw data	GM (1,1)	DGM (1,1)	ONGM	FNGM
Simulative stage				
6273				
7735	9051.12	9078.30	6375.82	8322.61
9943	10190.19	10220.02	8238.70	10119.95
10901	11472.62	11505.33	10145.79	11979.98
11764	12916.43	12952.28	12098.14	130904.89
14426	14541.95	14581.20	14096.81	15896.95
17804	16372.04	16414.99	16142.92	17958.48
19303	18432.45	18479.40	18237.59	20091.93
22096	20752.15	20803.44	20381.96	22299.80
24271	23363.79	23419.76	22577.22	24584.68
25364	26304.10	26365.12	24824.58	26949.25
27904	29614.44	29680.89	27125.27	29396.31
Verification stage				
31397	33341.38	33413.67	29480.56	31928.72
36192	37537.36	37615.90	31891.74	34549.47

Table 5: Comparison of prediction accuracies generated by these four models.

	Simulative stage			Verification stage		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
GM (1,1)	1102.30	1018.89	6.74	2326.18	1644.86	4.96
DGM (1,1)	1109.40	1027.54	6.84	2432.83	1720.27	5.18
ONGM	1146.33	1030.38	6.90	4395.89	3108.37	8.99
FGNM	1143.64	963.11	6.63	785.48	1087.11	3.12

APE values are much smaller than those of other models for training and testing periods.

Meanwhile, it is obvious to find from Figure 1 that the simulative and predictive values are relatively close to the curve of the raw data of natural gas consumption of China on the whole, meaning that high prediction is provided by the proposed model and also that the proposed model is a fairly appreciable forecasting model for natural gas consumption of China.

Now, we consider separately comparing three error indices, for simulative and verification stages, which are calculated and listed in Table 5. The MAPEs of these models GM (1,1), DGM (1,1), and FNGM (see Figure 2) for the simulative period are 6.74%, 6.84%, and 6.63%, decreasing to 4.96%, 5.18%, and 3.12% when it comes to the testing stage, respectively, except ONGM with an increase to 8.99% from 6.90%. This indicates all these models perform quite well. In other words, they all can be used to forecast future data of natural gas consumption of China. Nonetheless, the proposed model FNGM performs best among these four models, as it has the lowest MAPE values in training and testing stages. Additionally, a similar finding will be illustrated by the RMSE and MAE values in Table 5 because the FNGM model has the lowest RMSE and MAPE values in both training and testing periods. In summary, the four competing models have been shown to work quite well in forecasting the consumption of natural gas in China with

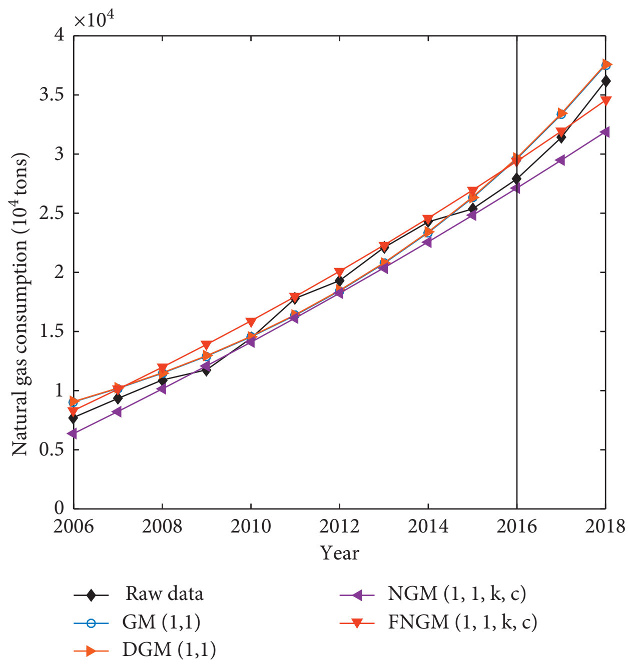

FIGURE 1: Curves of raw data and simulative data using these four models.

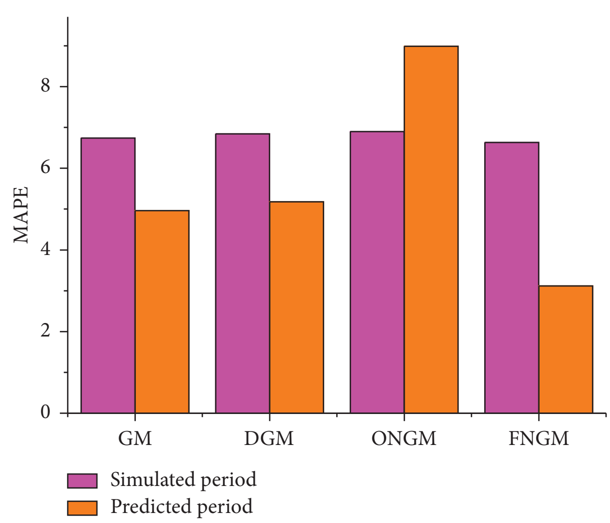

FIGURE 2: MAPE values generated from four different grey models.

TABLE 6: Forecasting results of China's natural gas consumption from 2019 to 2023.

Model	2019	2020	2021	2022	2023
GM	40825.94	45737.61	51240.19	57404.77	64310.99
DGM	40927.00	45851.60	51368.75	57549.77	64474.52
ONGM	37204.98	40669.13	44356.06	48230.10	52456.50
FNGM	39688.42	43280.69	47096.10	51148.50	55452.62

high prediction accuracies. It is, however, shown that the proposed model has a better prediction performance among these commonly used grey models than three error indices. Therefore, the proposed model has favorable accuracy, and the results have practical reference value.

Due to high prediction accuracy of the proposed model, it makes sense to apply this model to predict future natural gas consumption of China from 2019 to 2023. Note that in Table 6, it can be seen that China's natural gas consumption would increase year by year. In particular, aggregate natural gas consumption of China in 2023 will be up to approximate 55452.62×10^4 tons of SEC, which might help energy planning decision-makers make effective strategies to face chances and challenges caused by this change in advance.

6. Conclusion and Future Research

At present, we know that natural gas has become more and more crucial in energy market because of the hot topic of clean energy. For purpose of precise prediction of future natural gas consumption in order to help energy planning decision-makers make better strategies in advance, this paper studies how to increase prediction accuracy of the existing grey model in predicting natural gas consumption; we present a novel grey model based on the nonhomogeneous grey model, ONGM. Also, the product theory of the determinant is used to prove the fact that forecasting results are independent of the first entry of original series. This motivates a method, inserting an arbitrary number in front of the first entry to extract messages, and it is proposed to enhance forecasting ability, which is abbreviated as FNGM for simplicity. We apply the proposed model to predict future natural gas consumption from 2019 to 2023 after validating effectiveness of the proposed model. The numerical results show that the proposed model is a fairly appreciable model to predict China's natural gas consumption.

Up to this point, the potential advantages of the proposed model have been discussed in this paper; there exist, however, some issues that should be solved in future research. For example, empirically speaking, the model proposed to forecast that China's natural gas consumption is still a univariate model, meaning that we potentially ignore the effects of different factors on natural gas consumption. Therefore, the multivariate grey model will be concentrated in future work. Additionally, the model with fractional order accumulation and application of time-varying polynomial on grey control parameters will also be discussed in future research.

Data Availability

The data used to support the findings of this study are deposited at http://www.stats.gov.cn/english/.

Conflicts of Interest

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

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References

[1] Z.-G. Li, H. Cheng, and T.-Y. Gu, "Research on dynamic relationship between natural gas consumption and economic growth in China," *Structural Change and Economic Dynamics*, vol. 49, pp. 334–339, 2019.
[2] B. Soldo, "Forecasting natural gas consumption," *Applied Energy*, vol. 92, pp. 26–37, 2012.
[3] M. K. Hubbert, "Energy from fossil fuels," *Science*, vol. 109, no. 2823, pp. 103–109, 1949.
[4] M. K. Hubbert, "Nuclear energy and the fossil fuel," *Drilling and Production Practice*, American Petroleum Institute, New York, NY, USA, 1956.
[5] R. H. Brown, P. Kharouf, X. Feng, L.P. Piessens, and D. Nestor, "Development of feed-forward network models to predict gas consumption," in *Proceedings of 1994 IEEE International Conference on Neural Networks (ICNN'94)*, pp. 802–805, IEEE, Orlando, FL, USA, July 1994.
[6] R. Bartels, D. G. Fiebig, and D. Nahm, "Regional end-use gas demand in Australia," *Economic Record*, vol. 72, no. 219, pp. 319–331, 1996.
[7] F. B. Gorucu, "Evaluation and forecasting of gas consumption by statistical analysis," *Energy Sources*, vol. 26, no. 3, pp. 267–276, 2004.
[8] B. Lin and T. Wang, "Forecasting natural gas supply in China: production peak and import trends," *Energy Policy*, vol. 49, pp. 225–233, 2012.
[9] F. Shaikh and Q. Ji, "Forecasting natural gas demand in China: logistic modelling analysis," *International Journal of Electrical Power & Energy Systems*, vol. 77, pp. 25–32, 2016.
[10] Z. Wadud, H. S. Dey, M. A. Kabir, and S. I. Khan, "Modeling and forecasting natural gas demand in Bangladesh," *Energy Policy*, vol. 39, no. 11, pp. 7372–7380, 2011.
[11] B. Soldo, P. Potočnik, G. Šimunović, T. Šarić, and E. Govekar, "Improving the residential natural gas consumption forecasting models by using solar radiation," *Energy and Buildings*, vol. 69, pp. 498–506, 2014.
[12] B. C. Ervural, O. F. Beyca, and S. Zaim, "Model estimation of ARMA using genetic algorithms: a case study of forecasting natural gas consumption," *Procedia-Social and Behavioral Sciences*, vol. 235, pp. 537–545, 2016.
[13] A. Gascón and E. F. Sánchez-Úbeda, "Automatic specification of piecewise linear additive models: application to forecasting natural gas demand," *Statistics and Computing*, vol. 28, no. 1, pp. 201–217, 2018.
[14] N. Wei, C. Li, X. Peng, Y. Li, and F. Zeng, "Daily natural gas consumption forecasting via the application of a novel hybrid model," *Applied Energy*, vol. 250, pp. 358–368, 2019.
[15] A. Özmen, Y. Yılmaz, and G.-W. Weber, "Natural gas consumption forecast with MARS and CMARS models for residential users," *Energy Economics*, vol. 70, pp. 357–381, 2018.
[16] D. Sen, M. E. Günay, and K. M. M. Tunç, "Forecasting annual natural gas consumption using socio-economic indicators for making future policies," *Energy*, vol. 173, pp. 1106–1118, 2019.
[17] J. Chai, T. Liang, K. K. Lai, Z. G. Zhang, and S. Wang, "The future natural gas consumption in China: based on the LMDI-STIRPAT-PLSR framework and scenario analysis," *Energy Policy*, vol. 119, pp. 215–225, 2018.
[18] J. L. Deng, "Control problems of grey systems," *Systems & Control Letters*, vol. 1, no. 5, pp. 288–294, 1982.
[19] S. Ding, "A novel discrete grey multivariable model and its application in forecasting the output value of China's high-tech industries," *Computers & Industrial Engineering*, vol. 127, pp. 749–760, 2019.
[20] W. Q. Wu, X. Ma, B. Zeng, Y. Wang, and W. Cai, "Application of the novel fractional grey model FAGMO (1,1,k) to predict China's nuclear energy consumption," *Energy*, vol. 165, pp. 223–234, 2018.
[21] W.-Z. Wu and T. Zhang, "An improved gray interval forecast method and its application," *Communications in Statistics-Theory and Methods*, vol. 49, no. 5, pp. 1120–1131, 2020.
[22] Z.-X. Wang, Q. Li, and L.-L. Pei, "A seasonal GM (1,1) model for forecasting the electricity consumption of the primary economic sectors," *Energy*, vol. 154, pp. 522–534, 2018.
[23] U. Sahin, "Forecasting of Turkey's greenhouse gas emissions using linear and nonlinear rolling metabolic grey model based on optimization," *Journal of Cleaner Production*, vol. 239, Article ID 118079, 2019.
[24] L. Wu, S. Liu, D. Liu, Z. Fang, and H. Xu, "Modelling and forecasting CO_2 emissions in the BRICS (Brazil, Russia, India, China, and South Africa) countries using a novel multi-variable grey model," *Energy*, vol. 79, pp. 489–495, 2015.
[25] L. Kong and X. Ma, "Comparison study on the nonlinear parameter optimization of nonlinear grey Bernoulli model (NGBM (1,1)) between intelligent optimizers," *Grey Systems: Theory and Application*, vol. 8, no. 2, pp. 210–226, 2018.
[26] X. Ma, W. Q. Wu, and Y. Y. Zhang, "Improved GM (1, 1) model based on Simpson formula and its applications," *Journal of Grey System*, vol. 31, no. 4, pp. 33–46, 2019.
[27] Z. X. Wang, D. D. Li, and H. H. Zheng, "Model comparison of GM (1, 1) and DGM (1, 1) based on Monte-Carlo simulation," *Physica A: Statistical Mechanics and its Applications*, vol. 542, Article ID 123341, 2020.
[28] Z.-X. Wang, L.-Y. He, and H.-H. Zheng, "Forecasting the residential solar energy consumption of the United States," *Energy*, vol. 178, pp. 610–623, 2019.
[29] T. L. Tien, "The indirect measurement of tensile strength of material by the grey prediction model GMC (1,*n*)," *Measurement Science and Technology*, vol. 16, no. 6, 2005.
[30] C.-I. Chen, H. L. Chen, and S.-P. Chen, "Forecasting of foreign exchange rates of Taiwan's major trading partners by novel nonlinear Grey Bernoulli model NGBM (1,1)," *Communications in Nonlinear Science and Numerical Simulation*, vol. 13, no. 6, pp. 1194–1204, 2008.
[31] N.-M. Xie and S.-F. Liu, "Discrete grey forecasting model and its optimization," *Applied Mathematical Modelling*, vol. 33, no. 2, pp. 1173–1186, 2009.
[32] L. Wu, S. Liu, L. Yao, S. Yan, and D. Liu, "Grey system model with the fractional order accumulation," *Communications in Nonlinear Science and Numerical Simulation*, vol. 18, no. 7, pp. 1775–1785, 2013.
[33] J. Cui, S.-F. Liu, B. Zeng, and N.-M. Xie, "A novel grey forecasting model and its optimization," *Applied Mathematical Modelling*, vol. 37, no. 6, pp. 4399–4406, 2013.
[34] X. Ma, W. Wu, B. Zeng, Y. Wang, and X. Wu, "The conformable fractional grey system model," *ISA Transactions*, vol. 96, pp. 255–271, 2019.
[35] J. Wang, H. Jiang, Q. Zhou, J. Wu, and S. Qin, "China's natural gas production and consumption analysis based on the multicycle Hubbert model and rolling Grey model,"

Renewable and Sustainable Energy Reviews, vol. 53, pp. 1149–1167, 2016.

[36] X. Ma and Z. Liu, "Application of a novel time-delayed polynomial grey model to predict the natural gas consumption in China," *Journal of Computational and Applied Mathematics*, vol. 324, pp. 17–24, 2017.

[37] Y. H. Wu and H. Shen, "Grey-related least squares support vector machine optimization model and its application in predicting natural gas consumption demand," *Journal of Computational and Applied Mathematics*, vol. 338, pp. 212–220, 2018.

[38] F. Shaikh, Q. Ji, P. H. Shaikh, N. H. Mirjat, and M. A. Uqaili, "Forecasting China's natural gas demand based on optimised nonlinear grey models," *Energy*, vol. 140, pp. 941–951, 2017.

[39] B. Zeng and C. Li, "Forecasting the natural gas demand in China using a self-adapting intelligent grey model," *Energy*, vol. 112, pp. 810–825, 2016.

[40] T. L. Tien, "The indirect measurement of tensile strength by the new model FGMC (1,n)," *Measurement*, vol. 44, no. 10, pp. 1884–1897, 2011.

[41] L. Q. Zhan and H. J. Shi, "Methods and model of grey modeling for approximation non-homogenous exponential data," *Systems Engineering-Theory & Practice*, vol. 33, no. 3, pp. 689–694, 2013.

[42] X. Ma, Y.-S. Hu, and Z.-B. Liu, "A novel kernel regularized nonhomogeneous grey model and its applications," *Communications in Nonlinear Science and Numerical Simulation*, vol. 48, pp. 51–62, 2017.

[43] K. M. Abadir and J. R. Magnus, *Matrix Algebra*, Cambridge University Press, Cambridge, UK, 2005.

[44] Y. Zhang, Y. Xu, and Z. Wang, "GM (1,1) grey prediction of Lorenz chaotic system," *Chaos, Solitons & Fractals*, vol. 42, no. 2, pp. 1003–1009, 2009.