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
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 tech-
niques 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 includ-
ing 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
responding requirement on energy, especially on clean en-
ergy, 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 pro-
duction 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 Ban-
gladesh [10]. Soldo et al. [11] introduced solar radiation into the
residential natural gas consumption forecasting model to im-
prove 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, Gascón and Sánchez-Ubeda [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.

| 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-Ubeda [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                    |

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

be a nonnegative series and then the first-order accumulative generating operator series be
\[ X^{(1)} = \{ x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n) \}, \]  
(2)

where \( x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i), i = 1, 2, \ldots, n \). The differential equation
\[ \frac{dx^{(1)}(t)}{dt} + ax^{(1)}(t) = tb + c \]  
(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
\[ x^{(0)}(k) + ax^{(1)}(k) = kb + c, \]  
(4)

where \( z^{(1)}(k) \) is often called the background value, and further
\[ z^{(1)}(k) = 0.5(x^{(1)}(k - 1) + x^{(1)}(k)). \]  
(5)

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

\[ (a, b, c)' = (B'B)^{-1}B'Y, \]  
(6)

where
\[ B = \begin{bmatrix} -z^{(1)}(2) & 2 & 1 \\ -z^{(1)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & n & 1 \end{bmatrix}, \]  
(7)

\[ Y = [ x^{(0)}(2), x^{(0)}(3), \ldots, x^{(0)}(n) ]'. \]

As such, the solution to (3) with \( x^{(1)}(1) = x^{(0)}(1) \) can be acquired as follows:
\[ \tilde{x}^{(1)}(k) = \left( x^{(0)}(1) - \frac{b}{a} + \frac{c}{a^2} \right) e^{-a(k-1)} + \frac{b - \frac{b}{a} + \frac{c}{a^2}}{a}, \]  
(8)

The simulative values of \( X^{(0)} \) and \( \tilde{x}^{(0)} \) can be written as follows using the first-order inverse accumulative generating operator (IAOG):
\[ \tilde{x}^{(0)}(k) = \left( 1 - e^a \right) \left[ x^{(0)}(1) - \frac{b}{a} + \frac{b}{a^2} - \frac{c}{a} \right] e^{-a(k-1)} + \frac{b}{a} \]  
(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 \( \delta \), that is, \( x^{(0)}(1) + \delta \). Furthermore, we have \( X^{(1)} + \delta \). The matrix \( B \) and system parameters, respectively, become
\[ H = \begin{bmatrix} -z^{(1)}(2) - \delta & 2 & 1 \\ -z^{(1)}(3) - \delta & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) - \delta & n & 1 \end{bmatrix}, \]  
(10)

\[ (u, v, w)' = (H'H)^{-1}H'Y. \]  
(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
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:

\[
\begin{bmatrix} I & D \\ 0 & I \end{bmatrix} \begin{bmatrix} D & 0 \\ -I & E \end{bmatrix} = \begin{bmatrix} 0 & DE \\ -I & E \end{bmatrix},
\]

\[
\begin{bmatrix} D & 0 \\ -I & E \end{bmatrix} = \begin{bmatrix} 0 & DE \\ -I & E \end{bmatrix} = [DE].
\]

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

\[
|H' H| = \begin{bmatrix} H' & 0 \\ -I & H \end{bmatrix} = \begin{bmatrix} z_2 - \delta & z_3 - \delta & \cdots & z_n - \delta & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ 1 & 1 & \cdots & 1 & 0 & 0 & 0 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -1 & z_n - \delta & n & 1 \end{bmatrix},
\]

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

\[
|H' H| = [B' B],
\]

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

\[
u = \frac{1}{|H' H|} \begin{bmatrix} x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) \\ 2 & 3 & \cdots & n \end{bmatrix},
\]

\[
v = \frac{1}{|H' H|} \begin{bmatrix} z_2 - \delta & z_3 - \delta & \cdots & z_n - \delta & 0 & 0 & 0 \\ 2 & 3 & \cdots & n & 0 & 0 & 0 \\ -1 & 0 & \cdots & 0 & z_2 - \delta & 2 & 1 \\ 0 & -1 & \cdots & 0 & z_3 - \delta & 3 & 1 \\ \vdots & \vdots & \cdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & \cdots & -1 & z_n - \delta & n & 1 \end{bmatrix} = a,
\]

\[
u = \frac{1}{|H' H|} \begin{bmatrix} x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) \\ 1 & 1 & \cdots & 1 \end{bmatrix} = b,
\]

\[
u = \frac{1}{|H' H|} \begin{bmatrix} x^{(0)}(2) & x^{(0)}(3) & \cdots & x^{(0)}(n) \\ -1 & 0 & \cdots & 0 \end{bmatrix} = c + \delta a.
\]
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

\[
(1 - e^u) \left( x^{(0)}(1) + \delta - \frac{v}{u} + \frac{v}{u^2} - \frac{w}{u} \right) e^{-u(k-1)} + \frac{v}{u}
\]

\[
= (1 - e^a) \left( x^{(0)}(1) + \delta - \frac{b}{a} + \frac{b}{a^2} - \frac{c + \delta a}{a} \right) e^{-a(k-1)} + \frac{b}{a}
\]

\[
= \tilde{x}^{(0)}(k).
\]  

(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

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

(20)

The matrices \( B \) and \( Y \) are constructed as

\[
H = \begin{bmatrix}
-\tilde{z}^{(1)}(1) & 1 & 1 \\
-\tilde{z}^{(1)}(2) & 2 & 1 \\
\ldots & \ldots & \ldots \\
-\tilde{z}^{(1)}(n) & n & 1 \\
\end{bmatrix},
\]

(21)

\[
Y_R = \begin{bmatrix} x^{(0)}(1), x^{(0)}(2), \ldots, x^{(0)}(n) \end{bmatrix}^T.
\]

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

\[
\begin{bmatrix} a \\ b \\ c \end{bmatrix} = \left( H^T H \right)^{-1} H^T Y_R.
\]  

(22)

The time response function can be computed as

\[
\tilde{x}^{(1)}(k) = \left( x^{(0)}(0) - \frac{b}{a} + \frac{c}{a^2} \right) e^{-a(k-1)} + \frac{b}{a} + \frac{c}{a^2}.
\]  

(23)

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

\[
x^{(0)}(k) = \tilde{x}^{(1)}(k) - \tilde{x}^{(1)}(k - 1).
\]  

(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:

\[
\text{RMSE} = \sqrt{\frac{1}{n-1} \sum_{i=2}^{n} (e(i))^2},
\]

\[
\text{MAE} = \frac{1}{n-1} \sum_{i=2}^{n} |e(i)|,
\]

\[
\text{MAPE} = \frac{1}{n-1} \sum_{i=2}^{n} \left| \frac{e(i)}{x^{(0)}(k)} \right| \times 100%,
\]

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

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
APE values are much smaller than those of other models for training and testing periods. Meanwhile, it is obvious 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

### 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    | 1.76     | 1.77      | 0.84       | 1.37 |
| 1.11     | 2.06     | 2.07      | 1.46       | 2.04 |
| 1.92     | 2.40     | 2.42      | 2.06       | 2.67 |
| 2.24     | 2.81     | 2.82      | 2.65       | 3.27 |
| 3.03     | 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      | 11.44    | 11.63     | 10.86      | 10.06|
| MAPE     | 6.25     | 7.11      | 7.13       | 6.26 |
|          | 8.30     | 8.33      | 6.40       | 6.67 |
|          | 9.69     | 9.72      | 6.88       | 7.06 |
|          | 2.95     | 2.99      | 0.46       | 0.02 |
|          | 1.70     | 1.73      | 0.28       | 0.19 |
|          | 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 (1,1) | FNGM |
|----------|----------|-----------|------------|------|
| 6273     | 9051.12  | 9078.30   | 6375.82    | 8322.61|
| 7735     | 10190.19 | 10220.02  | 8238.70    | 10119.95|
| 9343     | 11472.62 | 11505.33  | 10145.79   | 11979.98|
| 10901    | 12916.43 | 12952.28  | 12098.14   | 130904.89|
| 11764    | 14541.95 | 14581.20  | 14096.81   | 15896.95|
| 14426    | 16372.04 | 16414.99  | 16142.92   | 17958.48|
| 17804    | 18432.45 | 18479.40  | 18237.59   | 20091.93|
| 19303    | 20752.15 | 20803.44  | 20381.96   | 22299.80|
| 22096    | 23363.79 | 23419.76  | 22577.22   | 24584.68|
| 24271    | 26304.10 | 26365.12  | 24824.58   | 26949.25|
| 25364    | 29614.44 | 29680.89  | 27125.27   | 29396.31|
| 27904    | 33431.38 | 33413.67  | 29480.56   | 31928.72|
| 31397    | 37537.36 | 37615.90  | 31891.74   | 34549.47|
| 36192    | 4143.64  | 4143.64   | 3281.25    | 3589.47|

### 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  |
| FNGM                | 1143.64 | 963.11  | 6.63  | 785.48  | 1087.11 | 3.12  |
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 $55452.62 \times 10^{4}$ 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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