Research Article

Application of Grey System Model to Forecast the Natural Gas Imports in China

Zhuan-Zhuan Shi,¹ Xiao-Yi Gou,² and Bo Zeng³

¹International Cooperation & Exchange Office, Chongqing Finance and Economics College, Chongqing 401320, China

²School of Management Science and Engineering, Chongqing Technology and Business University, Chongqing 400067, China

³Chongqing Key Laboratory of Spatial Data Mining and Big Data Integration for Ecology and Environment, Chongqing Finance and Economics College, Chongqing 401320, China

Correspondence should be addressed to Bo Zeng; bozeng@ctbu.edu.cn

Received 5 February 2021; Revised 13 March 2021; Accepted 17 March 2021; Published 2 April 2021

Academic Editor: Zhifeng Dai

Copyright © 2021 Zhuan-Zhuan Shi et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

China's natural gas imports will keep an upward trend in the future due to its increasing demands. A comparatively accurate prediction of natural gas imports will help the Chinese government make appropriate decisions when formulating energy policies. In this paper, a new grey predication model, GPM_NGI model, was proposed to forecast China's natural gas imports. Compared with GM (1, 1) and DGM (1, 1) model, the proposed new model performed better in the simulation process and bore smaller mean relative percentage error when used in simulating China's natural gas imports from 2011 to 2019. Then, the new model was employed to forecast China's natural gas imports from 2020 to 2022. The results showed that China's natural gas imports would continue to grow rapidly over the next three years. Therefore, in order to strike a balance between the natural gas supply and demand in the future and avoid overdependence on imports, the Chinese government should take effective measures from both the supply and demand ends, such as making better use of shale gas, wind, and solar energy as well as reducing the industrial dependence on natural gas.

1. Introduction

As one of the three most commonly-known fossil energy resources, natural gas is featured by its environmental friendliness, utilization security, and high heat production which coal and oil cannot be on par with when used in city gas and industrial fuel supply. It is globally acknowledged that natural gas is probably the most cost-efficient clean energy with low carbon. The recent years have witnessed a climbing growth rate of natural gas demands in China and the upward trend will continue in the next few years due to the following reasons. Firstly, the Chinese government highly emphasizes the importance of environmental conservation and stresses the use of “clean, low-carbon, safe, and cost-efficient” energies, which are clearly demonstrated in The 13th Five-Year Plan for Energy Development of People's Republic of China [1] and The CPC Central Committee's

Suggestions on the Formation of the 14th Five-Year Plan and the Long-Term Goals for the Year 2035 [2]. Natural gas, as one of the clean energies, will serve as “a bridge for the energy structure transformation in China” [3]. Secondly, the natural gas consumption in China keeps increasing in recent years, with the apparent consumption being 306.4 billion cubic meters in 2019 and an increasing rate of 8.6% compared with that of 2018, accounting for 8.1% of the primary energy consumption [4]. However, the average level of the proportion of natural gas consumption in the primary energy consumption worldwide is 24% [5], which means that there may be a great space for the natural gas demand growth in China in the future.

Both exploitation and importation are feasible ways for China to gratify its needs of natural gas. However, the exploitation of China's natural gas has been facing great challenges due to the scarcity of natural reserves, lack of

sophisticated technologies, and high cost of exploitation. Therefore, importation seems to become the best solution for China to strike the balance between the natural gas demand and supply in the foreseeable future. In 2018, China's natural gas import reached 125.4 billion cubic meters, ranking top in the world with a percentage of 9.8 in the global total natural gas imports. Meanwhile, China's dependence on natural gas importation reached as high as 45.3% in the same year [6].

As is mentioned above, the demand, consumption, and imports of natural gas in China are and will be increasing within a long duration of time. A comparatively accurate prediction of natural gas imports will help the Chinese government be fully aware of the real situation of China's natural gas demand and supply in the future, make early preparations for maintaining the balance between the two, and take effective measures to guarantee the sufficient supply of energy, avoiding the possible threats and risks that may be brought about by overdependence on natural gas and its imports. The results of this paper can also be valuable references for the scientific assessment of China's natural gas importation capacity and the formulation of related policies on China's natural resources exploitation and importation.

The prerequisite for forecasting China's natural gas imports in the future more accurately is a scientific and feasible mathematical model. Many scholars have adopted different models to predict the demands, production, and imports of natural gas. Shaikh used logistic modeling analysis to forecast the natural gas demands in China [7]. Mu and Li established a system dynamics model to forecast the demands and consumption of China's natural gas [8]. Zhang and Yang built up Bayesian Model Averaging to forecast the natural gas consumption in China [9]. Szoplik set up artificial neural networks to forecast natural gas consumption within a short period of time [10]. Bai developed a structure-calibrated support vector regression approach to forecast daily natural gas consumption [11]. As for imports of natural gas, fewer studies have been found compared with the other two research branches mentioned above. Wei, Cui, and Hu et al. employed a grey model to predict China's natural gas import demand through sea from 2018 to 2020 [12]. Li and Pu developed a new method based on genetic algorithm and extreme learning machine to predict China's natural gas imports from 2019 to 2028 [13]. A few combined models have also been proposed to forecast the natural gas consumption based on detailed analysis on its dominant influencing factors [14, 15]. Traditional prediction methods could explain the relationship between the consequences and influencing factors to some extent; however, due to lack of enough data and the complexity of factors that affect the demands and imports of natural gas imports in China, the prediction precision needs to be further improved.

The grey prediction model, one of the most important components of the grey system theory initiated by Professor Deng Julong in 1983, has been widely used and proved effective in solving uncertain problems with inaccurate data and incomplete information [16–20]. The grey prediction model has been successfully applied in the fields of energy, transportation, and agriculture as well as finance prediction

and optimization [21–25]. The basic model of grey prediction theory is GM (1, 1) model, a univariate grey prediction model with first-order derivative, which is most commonly used to predict issues of time sequence data with approximately homogeneous exponential growth [26]. In many cases, GM (1, 1) model did greatly improve the accuracy of prediction results; however, the error caused by discrete parameters but continuous time response function is always a problem [27]. Xie and Liu proposed discrete grey model, short for DGM (1, 1), which unifies parameter estimation and the model by making both of them in discrete form. DGM (1, 1) model can effectively eliminate the problems caused by the leap from the parameter estimation method based on difference equations to the time response function based on differential equations in modeling [28]. However, the shortcoming of DGM (1, 1) was quickly found by some diligent scholars. A few studies claimed that the growth rate of the simulation value in DGM (1, 1) model was constant, which was prone to large deviation in the simulation of nonhomogeneous exponential sequences [29–31]. To solve the problem, Zhan and Shi proposed a new grey model applicable to nonhomogeneous exponential sequences, NHGM (1, 1, k) model for short. The new model could simulate and predict all data sequences in accordance with nonhomogeneous exponential characteristics [32].

Since its very advent, NHGM (1, 1, k) model has been optimized a few times [33, 34] and applied in various practical problems. For example, Chen employed the unbiased NGM (1, 1, k) model to analyze and predict the landslide displacement in deformation monitoring [35]. Chen Nana et al. applied the unbiased nonhomogeneous grey model to evaluate the combined performance of science and finance in Hainan province, China [36]. The problem of the traditional NHGM (1, 1, k) model lies in the difficulty of iterating its time response function. In this paper, we will learn from the SIGM modeling of [37] and optimize the traditional NHGM (1, 1, k) model based on the discrete grey model of differential equation and then employ the optimized model to forecast China's natural gas imports in the years to come.

2. Grey Prediction Model of Natural Gas Imports

The classical GM (1, 1) model contains parameters a and b , with the former being called a development coefficient and the latter a grey actuating quantity. Indeed, the classical GM (1, 1) model is a two-parameter grey prediction model whose inherent structure makes it only applicable in the modeling and prediction of approximately homogeneous exponential sequences which often appear in an ideal state. The sequences with approximately nonhomogeneous exponential growth characteristics are more than common in our real life since the world is full of complexity and uncertainty.

In order to forecast China's natural gas imports in the future more scientifically and accurately, we learned from the modeling idea of SIGM model in [37], extended the basic form of GM (1, 1) model [$x^{(1)}(k) + az^{(1)}(k) = b$], and constructed a new grey prediction model which is suitable

for the modeling and prediction of nonhomogeneous exponential sequences. The new model has proved to be more superior in its structure and modeling capability. To make it more convenient to write and read, the new grey prediction model of natural gas imports will be abbreviated as GPM_NGI in the following parts.

2.1. The Basic Form of GPM_NGI Model

Definition 1. Let $G^{(0)} = (g^{(0)}(1), g^{(0)}(2), \dots, g^{(0)}(n))$, $g^{(0)}(k) \geq 0$, $k = 1, 2, \dots, n$, $G^{(1)}$ be the 1-AGO sequence of $G^{(0)}$; that is,

$$G^{(1)} = (g^{(1)}(1), g^{(1)}(2), \dots, g^{(1)}(n)), \quad (1)$$

where $g^{(1)}(k) = \sum_{i=1}^k g^{(0)}(i)$, $k = 1, 2, \dots, n$. And $Z^{(1)}$ is called the mean sequence generated by consecutive neighbors of $G^{(1)}$, i.e.,

$$Z^{(1)} = (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(n)), \quad (2)$$

where $z^{(1)}(k) = 0.5 \times [g^{(1)}(k) + g^{(1)}(k-1)]$, $k = 2, 3, \dots, n$; then,

$$g^{(0)}(k) + az^{(1)}(k) = kb + c, \quad (3)$$

is a differential equation with first derivative and one variable [37, 38]. The parameter a is called a development coefficient, which reflects the trend of the system- $g^{(0)}(k)$. The parameter b is called a grey actuating quantity, which represents all the grey information that may affect the development of the system. kb means that the value of b is linearly correlated with the time point- k . The parameter c is called a random disturbance term or random error term, which is used to represent the information with accidentness or weak influences beyond the dominant variables.

2.2. Parameter Estimation of GPM_NGI Model.

Parameter estimation is one of the most important steps in constructing the grey prediction model. Its basic idea is to use the least square method to estimate the parameters a , b , and c of GPM_NGI model on the condition that the square sum of the simulation error of the original sequence is the smallest.

Theorem 1 (see [37]). Let $G^{(0)}$, $G^{(1)}$, and $Z^{(1)}$ be just like Definition 1, and $\hat{p} = (a, b, c)^T$ is the parameter vector, and

$$Y = \begin{bmatrix} g^{(0)}(2) \\ g^{(0)}(3) \\ \vdots \\ g^{(0)}(n) \end{bmatrix}, \quad (4)$$

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

and then the parameter vector of equation (3) can be estimated using the least square method, which satisfies

$$\hat{p} = (a, b, c)^T = (B^T B)^{-1} B^T Y. \quad (5)$$

Proof. Substituting $G^{(0)}$, $G^{(1)}$, and $Z^{(1)}$ into equation (3), we can obtain

$$\begin{cases} g^{(0)}(2) + az^{(1)}(2) = 2b + c, \\ g^{(0)}(3) + az^{(1)}(3) = 3b + c, \\ \vdots \\ g^{(0)}(n) + az^{(1)}(n) = nb + c, \end{cases} \quad (6)$$

and equation (6) can also be expressed as

$$Y = B\hat{p}. \quad (7)$$

Replacing $g^{(0)}(k)$ with $-az^{(1)}(k) + kb + c$, we can get an error sequence, that is,

$$\varepsilon = Y - B\hat{p}, \quad (8)$$

Assuming that

$$s = \varepsilon^T \varepsilon = (Y - B\hat{p})^T (Y - B\hat{p}) = \sum_{k=2}^n [g^{(0)}(k) + az^{(1)}(k) - kb - c]^2, \quad (9)$$

the parameter vector $\hat{p} = (a, b, c)^T$ that minimizes s should satisfy

$$\begin{cases} \frac{\partial s}{\partial a} = 2 \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c)z^{(1)}(k) = 0, \\ \frac{\partial s}{\partial b} = -2 \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c)k = 0, \\ \frac{\partial s}{\partial c} = -2 \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c) = 0. \end{cases} \quad (10)$$

After combining, we obtain

$$\begin{cases} \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c)z^{(1)}(k) = 0, \\ \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c)k = 0, \\ \sum_{k=2}^n (g^{(0)}(k) + az^{(1)}(k) - kb - c) = 0. \end{cases} \quad (11)$$

According to equation (11), we get

$$\begin{aligned} B^T \varepsilon = 0 &\implies B^T (Y - B\hat{p}) = 0 \implies B^T Y - B^T B\hat{p} \\ &= 0 \implies \hat{\sigma} = (B^T B)^{-1} B^T Y. \end{aligned} \quad (12)$$

End of proof. $\square$

2.3. The Time Response Function of GPM_NGI Model. Parameter estimation is the very first step of constructing a grey prediction model. It is obvious that the basic form of GPM_NGI model, $g^{(0)}(k) + az^{(1)}(k) = kb + c$, solely cannot realize the forecasting of the development trend of the system $\hat{g}^{(0)}(k)$. The time response function of GPM_NGI model, which shows the functional relationship between the system $\hat{g}^{(0)}(k)$ and the time point k , needs to be established to calculate the value of $\hat{g}^{(0)}(k)$ at different time points.

According to Definition 1, we know that

$$g^{(1)}(k) = \sum_{i=1}^k g^{(0)}(i), \quad k = 1, 2, \dots, n, \quad (13)$$

so

$$g^{(0)}(k) = g^{(1)}(k) - g^{(1)}(k-1), \quad k = 2, 3, \dots, n, \quad (14)$$

and

$$z^{(1)}(k) = 0.5 \times (g^{(1)}(k) + g^{(1)}(k-1)), \quad k = 2, 3, \dots, n. \quad (15)$$

Substituting equations (14) and (15) into equation (3), when $k = 2, 3, \dots, n$, we can obtain

$$g^{(1)}(k) - g^{(1)}(k-1) + 0.5a \times (g^{(1)}(k) + g^{(1)}(k-1)) = kb + c. \quad (16)$$

The above equation can be recast as

$$g^{(1)}(k) = \frac{1-0.5a}{1+0.5a} g^{(1)}(k-1) + \frac{b}{1+0.5a} k + \frac{c}{1+0.5a}. \quad (17)$$

According to equation (17), when $k = 2, 3$, we can obtain

$$\hat{g}^{(1)}(2) = \frac{1-0.5a}{1+0.5a} g^{(1)}(1) + 2 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a}, \quad (18)$$

$$\hat{g}^{(1)}(3) = \frac{1-0.5a}{1+0.5a} \hat{g}^{(1)}(2) + 3 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a}. \quad (19)$$

Substituting equation (18) into equation (19), after being reorganized, we can get

$$\hat{g}^{(1)}(3) = \left(\frac{1-0.5a}{1+0.5a} \right)^2 g^{(1)}(1) + \frac{1-0.5a}{1+0.5a} \left(2 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right) + \left(3 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right). \quad (20)$$

Similarly, if we put $g^{(1)}(u-1)$ into $g^{(1)}(u)$ ($u = 2, 3, \dots, n$), after being rearranged, we can get

$$\begin{aligned} \hat{g}^{(1)}(u) &= \left(\frac{1-0.5a}{1+0.5a} \right)^{(u-1)} g^{(1)}(1) + \left(\frac{1-0.5a}{1+0.5a} \right)^{(u-2)} \left(2 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right) + \dots \\ &\quad + \left(\frac{1-0.5a}{1+0.5a} \right)^{(1)} \left((u-1) \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right) + \left(\frac{1-0.5a}{1+0.5a} \right)^{(0)} \left(u \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right), \end{aligned} \quad (21)$$

and equation (21) can be simplified as

$$\begin{aligned}\hat{g}^{(1)}(u) &= g^{(1)}(1) \cdot \left(\frac{1-0.5a}{1+0.5a}\right)^{(u-1)} \\ &+ \sum_{h=0}^{u-2} \left[(u-h) \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right] \cdot \left(\frac{1-0.5a}{1+0.5a}\right)^h.\end{aligned}\quad (22)$$

$$\begin{aligned}\hat{g}^{(0)}(k) &= g^{(1)}(1) \cdot \left(\frac{1-0.5a}{1+0.5a}\right)^{(k-1)} + \sum_{h=0}^{k-2} \left[(k-h) \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right] \cdot \left(\frac{1-0.5a}{1+0.5a}\right)^h \\ &- \sum_{h=0}^{k-3} \left[(k-h-1) \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a} \right] \cdot \left(\frac{1-0.5a}{1+0.5a}\right)^h.\end{aligned}\quad (23)$$

After rearranging equation (23), we can obtain

$$\hat{g}^{(0)}(k) = \left[x^{(0)}(1) \left(\frac{1-0.5a}{1+0.5a} - 1\right) + \left(2 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a}\right) \right] \left(\frac{1-0.5a}{1+0.5a}\right)^{(k-2)} + \sum_{h=0}^{k-3} \frac{b}{1+0.5a} \left(\frac{1-0.5a}{1+0.5a}\right)^{(h)}.\quad (24)$$

Let

$$\alpha = g^{(0)}(1) \left(\frac{1-0.5a}{1+0.5a} - 1\right) + \left(2 \cdot \frac{b}{1+0.5a} + \frac{c}{1+0.5a}\right),\quad (25)$$

$$\beta = \frac{1-0.5a}{1+0.5a}, \gamma = \frac{b}{1+0.5a}.\quad (26)$$

and equation (24) can be simplified as

$$\hat{g}^{(0)}(k) = \alpha \beta^{(k-2)} + \sum_{h=0}^{k-3} \gamma \beta^h.\quad (27)$$

Then, equation (27) is called the time response function of GPM_NGI model, $k = 2, 3, \dots, n$. When $k = 2, 3, \dots, n$, $\hat{g}^{(0)}(k)$ is called simulated values and when $t = n+1, n+2, \dots$, $\hat{g}^{(0)}(k)$ is called predicted values [35].

3. Forecasting of China's Natural Gas Imports

Natural gas imports are affected by not only the demand and supply as well as energy structure, but also the related national policies. The data are full of uncertainty since the real

According to Definition 1, we know that $\hat{g}^{(0)}(k) = \hat{g}^{(1)}(k) - \hat{g}^{(1)}(k-1)$, so

situation is far more than complicated. The statistical data of natural gas imports from 2011 to 2019 (see Table 1) will serve as modeling sample in this paper.

Data from China Energy Website (<http://www.china5e.com/>).

3.1. The Construction of GPM_NGI Model for China's Natural Gas Imports Forecasting.

- (i) Select experimental data for constructing GPM_NGI model of China's natural gas imports forecasting.

From Table 1, we can see that the data available are limited, so all the data will be used to do modeling. The original sequence is

$$\begin{aligned}G^{(0)} &= (g^{(0)}(1), g^{(0)}(2), \dots, g^{(0)}(9)) \\ &= (312, 421, 525, 591, 611, 746, 946.3, 1254, 1340).\end{aligned}\quad (28)$$

According to Definition 1, we can get

$$\begin{aligned}G^{(1)} &= (g^{(1)}(1), g^{(1)}(2), \dots, g^{(1)}(9)) \\ &= (312, 733, 1258, 1849, 2460, 3206, 4152.3, 5406.3, 6746.3) \\ Z^{(1)} &= (z^{(1)}(2), z^{(1)}(3), \dots, z^{(1)}(9)) \\ &= (522.5, 995.5, 1553.5, 2154.5, 2833, 3679.15, 4779.3, 6076.3).\end{aligned}\quad (29)$$

TABLE 1: China's Natural Gas Imports from 2011 to 2019 (unit: 100 million cubic meters).

Year	2011	2012	2013	2014	2015	2016	2017	2018	2019
Production	312.0	421.0	525.0	591.0	611.0	746.0	946.3	1254.0	1340.0

(ii) Calculate the parameters of GPM_NGI model for China's natural gas imports forecasting; to check the simulation and prediction performance of GPM_NGI model, we grouped the raw data into two categories. Specifically, the first seven numbers were used as simulation data for the model building

while the remaining two were used as reserved data to test the prediction error of the model.

According to Theorem 1, the parameter matrix can be set up and the parameter vector, $\hat{p} = (a, b, c)^T$, can be calculated as follows:

$$B = \begin{bmatrix} -z^{(1)}(2) & 2 & 1 \\ -z^{(1)}(3) & 3 & 1 \\ \vdots & \vdots & \vdots \\ -z^{(1)}(n) & n & 1 \end{bmatrix} = \begin{bmatrix} -522.5 & 2 & 1 \\ -995.5 & 3 & 1 \\ \vdots & \vdots & \vdots \\ -3679.15 & 7 & 1 \end{bmatrix}, Y = \begin{bmatrix} g^{(0)}(2) \\ g^{(0)}(3) \\ \vdots \\ g^{(0)}(n) \end{bmatrix} = \begin{bmatrix} 421 \\ 525 \\ \vdots \\ 946.3 \end{bmatrix}. \quad (30)$$

The values of the parameter vector are shown below:

$$\begin{aligned} \hat{p} &= (a, b, c)^T = (B^T B)^{-1} B^T Y, \\ &= (-0.3525, -125.9916, 517.3421). \end{aligned} \quad (31)$$

(iii) Construct the time response function of GPM_NGI model for China's natural gas imports forecasting.

As shown in Section 2.3, substitute the values of the parameter vector into equations (25) and (26), and we can get the values of α, β, γ .

$$\begin{aligned} \alpha &= g^{(0)}(1) \left(\frac{1 - 0.5a}{1 + 0.5a} - 1 \right) + \left(2 \cdot \frac{b}{1 + 0.5a} + \frac{c}{1 + 0.5a} \right) = 455.6647, \\ \beta &= \frac{1 - 0.5a}{1 + 0.5a} = 1.4280, \\ \gamma &= \frac{b}{1 + 0.5a} = -152.9514. \end{aligned} \quad (32)$$

Substituting α, β, γ into equation (27), we can obtain the time response function of GPM_NGI model:

$$\begin{aligned} \hat{g}^{(0)}(k) &= \alpha \beta^{(k-2)} + \sum_{h=0}^{k-3} \gamma \beta^h = 455.6647 \\ &\quad \times 1.4280^{k-2} - 152.9514 \sum_{h=0}^{k-3} 1.4280^h. \end{aligned} \quad (33)$$

3.2. Simulation of China's Natural Gas Imports.

According to equation (33), the simulation value and simulation error of GPM_NGI model can be calculated when $k = 2, 3, \dots, 9$. At the same time, we also employed GM (1, 1) model and DGM (1, 1) model to simulate China's natural gas imports as comparison. Their simulated data and simulated errors are shown in Table 2 and Figure 1, respectively.

As can be seen from Figures 1(a) and 1(b), GPM_NGI model has better global performances than GM (1, 1) and

DGM (1, 1) all through the eight year. Figure 1(b) indicates that GPM_NGI model bears the smallest mean relative prediction percentage error compared with the other two. Besides, compared with DGM (1, 1) model and GM (1, 1) model, GPM_NGI model has the smallest global mean relative simulation error. In general, GPM_NGI model performs best in the forecast of China's natural gas imports, indicating that it can be used to forecast China's natural gas imports in the medium term.

3.3. Forecasting of China's Natural Gas Imports. Due to the better performance of GPM_NGI model in simulation capability, we applied it to the forecasting of China's natural gas imports from 2020 to 2022, the results of which can be found in Table 3. Based on the real values of natural gas imports from 2011 to 2019 and the predictive values of natural gas imports from 2020 to 2023, the line chart of China's natural gas imports from 2011 to 2022 is drawn in Figure 2.

TABLE 2: Simulation of different models for China's natural gas imports from 2012 to 2019.

k	Real value	GPM_NGI		DGM (1, 1)		GM (1, 1)	
		Simulated value	Simulation error (%)	Simulated value	Simulation error (%)	Simulated value	Simulation error (%)
Data for simulation							
2	421	455.66	8.2339	421.36	0.0846	419.58	0.3374%
3	525	497.72	5.1961	490.94	6.4882	489.00	6.8568%
4	591	557.77	5.6220	572.01	3.2136	569.91	3.5685%
5	611	643.53	5.3238	666.47	9.0779	664.21	8.7080%
6	746	765.98	2.6786	776.52	4.0916	774.10	3.7672%
7	946.3	940.84	0.5767	904.75	4.3903	902.18	4.6620%
Mean relative simulation percentage error			4.6052		4.5577		4.65
Data for prediction							
8	1254	1190.54	5.0610	1054.16	15.9361	1051.46	16.1519%
9	1340	1547.09	15.4543	1228.24	8.3403	1225.43	8.5503%
Mean relative prediction percentage error			10.2576		12.1382		12.3511
Global mean relative percentage error			6.0183		6.4528		6.5752

(a)

FIGURE 1: Continued.

FIGURE 1: Comparison of simulation percentage errors by different models. (a) Year. (b) The type of model.

TABLE 3: The predicted China's natural gas Imports from 2020 to 2022 (unit: 100 million cubic meters).

Year	2020	2021	2022
Production	2056.23	2783.27	3821.45

FIGURE 2: Line chart of China's natural gas imports from 2011 to 2022.

4. Conclusion

The forecast results showed that China's natural gas imports would continue to keep an upward trend in the next few years, with the imports being 382.15 billion cubic meters in 2022, 12 times as much as that of 2011. This is mainly because natural gas is a kind of clean energy, which is in line with the concept of green development advocated by the Chinese government in recent years. Besides, China's GDP growth rate still keeps higher than 6% despite of its slowing down in economic development recently, which leads to the increase of natural gas imports as before. Meanwhile, the increasing natural gas imports are closely related with the growing natural gas demands in China. Zeng et al. had predicted China's natural gas demands and the results showed that China's natural gas demand would be about 340 billion cubic meters in 2020 [37, 39]. The predictive result of the natural gas import in 2020 in this essay is 205.62 billion cubic meters, accounting for about 60% of the predictive demand in the same year. It shows that the supply of China's natural gas is still heavily dependent on imports and its production is insufficient. Although the trend of trade globalization is inevitable and keeps accelerating in recent years, we have to realize the threats and risks that overdependence on natural gas imports may bring to China's energy security and industrial development since the global energy geopolitical game is increasingly fiercer.

In order to reduce the risks of overdependence on natural gas imports, China can take effective measures from both the supply and demand ends. From the perspective of supply, the idea of diversified energy consumption should be advocated and unconventional energy, such as shale gas, solar energy, and wind energy, can be further exploited and utilized. Firstly, China is abundant in recoverable shale gas reserves, covering 20% of the world total. Therefore, increasing the utilization of shale gas, such as cultivating industrial clusters for shale gas utilization and offering governmental support, can effectively alleviate the pressure of natural gas supply. Secondly, China started early in the field of solar power generation, but there are some problems in the solar photovoltaic industry, such as raw materials' overdependence on imports, lack of core technology and equipment, and insufficient development of domestic market, etc. Hence we need to increase investment in science and technology to overcome technical difficulties in solar energy development and carry out favorable policies to enhance the market vitality. Thirdly, as one of the most important unconventional energy resources with rich reserves and wide distribution, wind energy should be made better use of. However, the prerequisite to fully develop wind energy is to fully understand its strong random volatility and the difficulty in accurate prediction. The utilization rate of wind power energy could be improved only if the prediction precision of wind power was improved. In terms of demand, the government should give more favorable policies to encourage industrial enterprises to use unconventional energies since natural gas is limited in the final analysis. Besides, the utilization rate of the existing natural gas can be improved through technological innovation, which is also a consideration of reducing the huge demand for natural gas from the very beginning.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

Acknowledgments

This work was supported by Chongqing Natural Science Foundation of China (Grant nos. Cstc2019jcyj-msxmX0003), the Key Project of Scientific and Technological Research of Chongqing Education Commission (Grant Nos. KJZD-K202000804), and Chongqing Overseas Students Entrepreneurship and Innovation Support Program (Grant no. Cx2019048).

References

- [1] National Development and Reform Commission of PRC, *The 13th Five-Year Plan for Energy Development of People's Republic of China*[EB/OL], National Development and Reform Commission of PRC, Beijing, China, 2016, https://www.sohu.com/a/124859797_470071.
- [2] *The CPC Central Committee's Suggestions on the Formation of the 14th Five-Year Plan and the Long-Term Goals for the Year 2035*[EB/OL], China Net Finance, Beijing, China, 2020, <https://baijiahao.baidu.com/s?id=1682389302721903220>.
- [3] P. Liu, G. Liu, J. Han et al., "Brief Analysis about the role of natural gas in China's energy transformation," *Science Technology and Industry*, vol. 14, no. 6, pp. 136–138, 2014.
- [4] China Commerce Research Institute, *An Analysis of China's Natural Gas Consumption in 2019*, China Commerce Research Institute, Beijing, China, 2020, <https://baijiahao.baidu.com/s?id=1678166707244029004>.
- [5] British Petroleum, *Statistical Review of World Energy 2018* [EB/OL], http://www.bp.com/zh_cn/china/reports-and-publications.html, British Petroleum, London, UK, 2018, http://www.bp.com/zh_cn/china/reports-and-publications.html.
- [6] National Development and Reform Commission of PRC, *China's Natural Gas Import Ranks First in the World in 2018 and the Natural Gas Market Is Still on the rise*[EB/OL], National Development and Reform Commission of PRC, Beijing, China, 2019, <http://free.chinabaogao.com/nengyuan/201901/01213944092019.html>.
- [7] 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.
- [8] X. Ma and G. Li, "Study on natural gas consumption forecast and influence factors in China based on system dynamics model," *Journal of Engineering Studies*, vol. 10, pp. 56–67, 2018.
- [9] W. Zhang and J. Yang, "Forecasting natural gas consumption in China by bayesian model averaging," *Energy Reports*, vol. 1, pp. 216–220, 2015.
- [10] J. Szoplik, "Forecasting of natural gas consumption with artificial neural networks," *Energy*, vol. 85, no. 1, pp. 208–220, 2015.

- [11] Y. Bai and C. Li, "Daily natural gas consumption forecasting based on a structure-calibrated support vector regression approach," *Energy and Buildings*, vol. 127, pp. 571–579, 2016.
- [12] S. Wei, W. Cui, X. Hu et al., "Prediction of China's natural gas import demand through sea based on grey model," *Natural Gas Technology and Economy*, vol. 13, no. 1, pp. 8–12, 2019.
- [13] H. Li and G. Pu, "Forecasting of China's natural gas import Based on GA-ELM model," *Henan Science*, vol. 38, no. 4, pp. 667–673, 2020.
- [14] D. Wang, Y. Liu, Z. Wu et al., "Scenario analysis of natural gas consumption in China based on wavelet neural network optimized by particle swarm optimization algorithm," *Energies*, vol. 11, no. 4, pp. 8–25, 2018.
- [15] D. E. Gejirifu and W. Gao, "Forecasting China's natural gas consumption based on adaboost-particle swarm optimization-extreme learning machine integrated learning methods," *Energies*, vol. 11, no. 11, pp. 1–20, 2018.
- [16] C. Fan and Y. Guo, "Forecasting the Chinese grain yield using hybrid ARIMA and error-corrected grey model based on the Wavelet Transform," *Journal of Grey System*, vol. 31, no. 4, pp. 97–110, 2019.
- [17] Q. Wang and F. Jiang, "Integrating linear and nonlinear forecasting techniques based on grey theory and artificial intelligence to forecast shale gas monthly production in Pennsylvania and Texas of the United States," *Energy*, vol. 178, pp. 781–803, 2019.
- [18] B. Zeng and C. Luo, "Forecasting the total energy consumption in China using a new-structure grey system model," *Grey Systems: Theory and Application*, vol. 7, no. 2, pp. 194–217, 2017.
- [19] B. Zeng, M. Y. Tong, J. Kang, and X. Ma, "A new-structure grey Verhulst model: development and performance comparison," *Applied Mathematical Modelling*, vol. 81, pp. 522–537, 2020.
- [20] B. Zeng, M. Duan, and Y. F. Zhou, "A new multivariable grey prediction model with structure compatibility," *Applied Mathematical Modelling*, vol. 75, pp. 385–397, 2019.
- [21] Z. Dai, H. Zhuo, J. Kang, and F. Wen, "The skewness of oil price returns and equity premium predictability," *Energy Economics*, vol. 94105069 pages, 2021.
- [22] Z. Dai and J. Kang, "Some new efficient mean-variance portfolio selection models," *International Journal of Finance & Economics*, vol. 26, 2021.
- [23] B. Zeng and H. Li, "Prediction of coalbed methane production in China based on an optimized grey system model," *Energy & Fuels*, vol. 35, pp. 4333–4344, 2021.
- [24] B. Zeng, H. Li, and X. Ma, "A novel multi-variable grey forecasting model and its application in forecasting the grain production in China," *Computers & Industrial Engineering*, vol. 150, Article ID 106915, 2020.
- [25] B. Zeng, X. Ma, and M. Zhou, "A new-structure grey Verhulst model for China's tight gas production forecasting," *Applied Soft Computing*, vol. 96, Article ID 106600, 2020.
- [26] S. Liu, Bo Zeng, J. Liu et al., "Several basic models of GM (1, 1) and their applicable bound," *Systems Engineering and Electronics*, vol. 36, no. 3, pp. 501–508, 2014.
- [27] Z. Guoyan and Y. Wei, "Broad discrete grey model and its application," *Systems Engineering-Theory & Practice*, vol. 40, no. 3, pp. 736–747, 2020.
- [28] X. Naiming and S. Liu, "Discrete GM (1, 1) and mechanism of grey forecasting model," *Systems Engineering-Theory & Practice*, vol. 1, pp. 93–99, 2005.
- [29] T. Yao and S. Liu, "Improvement of a forecasting discrete GM (1, 1)," *Systems Engineering*, vol. 25, no. 9, pp. 103–106, 2007.
- [30] S. Ding, R. Li, and Z. Tao, "A novel adaptive discrete grey model with time-varying parameters for long-term photovoltaic power generation forecasting," *Energy Conversion and Management*, vol. 227, 2020.
- [31] X. Kong, Y. Zhao, and J. Chen, "Non-equidistance DGM (1, 1) model based on the concave sequence and its application to predict the China's per capita natural gas consumption," *Journal of Systems Science and Information*, vol. 6, no. 4, pp. 376–384, 2018.
- [32] L. Zhan and H. 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.
- [33] F. Chen and Y. Wei, "Approximate non-homogeneous index sequence GM (1, 1) model of grey derivative optimization," *Systems Engineering-Theory & Practice*, vol. 33, no. 11, pp. 2874–2878, 2013.
- [34] Y. Dang, Z. Liu, and J. Ye, "Direct modeling method of unbiased non-homogeneous grey prediction model," *Control and Decision*, vol. 32, no. 5, pp. 823–828, 2017.
- [35] P. Chen, "Application of an unbiased model in deformation monitoring," *Science of Surveying and Mapping*, vol. 43, no. 3, pp. 117–122, 2018.
- [36] N. Chen, Z. Bai, and He Wenfeng, "Research on the evaluation of technology and finance performance based on unbiased non-homogeneous grey model," *Mathematics in Practice and Theory*, vol. 50, no. 18, pp. 288–295, 2020.
- [37] Bo Zeng, X. Ma, and J. Shi, "A new-structure grey Verhulst model for China's tight gas production forecasting," *Applied Soft Computing*, vol. 96, Article ID 106600, 2020.
- [38] S. Liu and Yi Lin, *Grey Systems Theory and applications*, Springer-Verlag, Berlin, Germany, 2010.
- [39] S. Ding, "A novel self-adapting intelligent grey model for forecasting China's natural-gas demand," *Energy*, vol. 162, pp. 393–407, 2018.