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Article

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Research paper

Application of a new grey prediction model and grey average weakening buffer operator to forecast China's shale gas output

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ABSTRACT

Scientifically and accurately forecasting of future shale gas output tends to be very important in making energy policies, especially for China whose historical data of shale gas output is very limited. The existing grey shale gas output prediction model does not perform well in prediction due to its defects. To overcome these shortcomings, this paper, based on the principle of “new information priority”, combined with the contradiction between model prediction results and qualitative data analysis conclusions, designs a grey prediction model combining new initial conditions and original data reprocessing. Then the new model's accumulative order is optimized by fraction accumulation generation operation and its properties are discussed. Finally, the new model is used to simulate and forecast shale gas output in China from 2012 to 2018 and compared it with the existing shale gas prediction model. The comparison results show that the new model reduces by 84.34%, 68.96% and 75.60% of the mean relative simulation percentage error (MRSPE), mean relative prediction percentage error (MRPPE) and comprehensive mean relative percentage error (CMPPE) respectively. This paper not only has theoretical innovations but also provides a good mathematical method for predicting shale gas output.

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1. Introduction

China's shale gas resource has a deep mining potential than other countries (Ma et al., 2017; Zou et al., 2016), but its development level is still low now (Zhao et al., 2015). With the high speed of Chinese economic growth, the demand for shale gas resource is constantly increasing. It poses a great challenge to energy development and can even be a threat to national energy security. A Scientific and accurate prediction methods for China's shale gas output, can grasp the development potential of China's shale gas resources, and have great significance for promoting the Chinese government to rationally formulate energy policies and guaranteeing China's energy supply.

Before choosing a suitable mathematical model to forecast China's shale gas output, we searched the relevant literature on Web of Science by entering the key words “shale gas” and “forecasting”, and there are lots relevant research were founded. However, most of these studies are focused on the shale gas reservoir or exploration mechanism (Fan et al., 2020; Kovalchuk and Hadjistassou, 2020). The research of shale gas output is

mainly to study the daily or monthly production of shale gas with large sample characteristics from a microscopic perspective (Wang and Jiang, 2019; Wang et al., 2018). The methods used are large-sample learning methods such as machine learning and statistics.

Currently, the exploiting of China's shale gas is still in initial stage (Wang et al., 2019; Chen et al., 2018), and the historical data of shale gas output is very limited (only seven years data) (Sang et al., 2016). The complex geological conditions surrounding (Dong et al., 2015; Guo, 2016), immature shale gas exploration technology (Yu, 2015; Wu et al., 2015b), and unclear formation mechanism (Cui et al., 2019), make prediction of shale gas in China highly uncertain (Li et al., 2016). Hence, the above machine learning and statistical prediction models based on big data cannot effectively simulate and predict with limited data and uncertainties.

The grey system theory was proposed by professor Deng Ju-long in 1982, which aimed to process the “small data” and “poor information” uncertainty problems (Deng, 1982). In 2018, based on the grey system theory, Bo Zeng et al. developed a grey unbiased prediction model (abbreviated as UGM(1,1)), to forecast the output of China's shale gas, which shown a relative good simulation result (Zeng et al., 2018). But the poor prediction result is not ideal. The latest data shows that the actual value of China's

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shale gas output in 2017 and 2018 are 89.95 and 108.81 hundred million cubic meters (Hmcm) respectively. However, in Ref. Zeng et al. (2018), the prediction value of China's shale gas output in 2017 and 2018 are 106.581 and 146.358 Hmcm, which the prediction errors reach 18.49% and 34.51%. It apparently indicates the performance of UGM(1,1) is not ideal and this model cannot be used to forecast the output of China's shale gas.

Why there are such big difference between the simulation effect and prediction effect of UGM(1,1) model? The major reasons are as follows: (i) The initial value is used as the iterative base value to derive the time response function of the prediction model to guide the influence of the model error stacking degree, which in turn affects the modeling effect of the model. The initial value selection of the UGM(1,1) model is calculated based on the principle of minimum simulation error. However, according to the principle of new information priority in grey system theory, the last data has the greatest impact on the trend of the sequence (Xia et al., 2020; Li and Wei, 2012). It means that the existing grey prediction model is upgraded simulation ability, but at the expense of some predictive ability. (ii) The modeling sequence of UGM(1,1) model is processed data by weighted grey weakening buffer operator. The setting of the weight of this buffer operator has strong subjectivity (Li et al., 2019; Liu et al., 2014), which is easy to be inconsistent with the actual situation and has a large subjective effect on the future prediction results. (iii) The accumulative generation technique is a unique method of the grey prediction method, and the accumulative generation order is an important factor affecting the stability of the grey model (Luo and An, 2019; Wu et al., 2019). The accumulative generation order of UGM(1,1) model is set to 1 order. However, between 0 and 1 order, there must also be a fractional order, through which the order of magnitude between the accumulated numbers can be precisely adjusted.

Based on the above analysis, a new shale gas output grey prediction model is established in this paper. The new model overcomes the deficiencies of the UGM(1,1) model, and has the following advantages:

(I) The fractional order accumulation technique and inverse fractional order accumulation technique are innovatively introduced in sequence generation process of the new model. The purpose of grey accumulation is to mine grey information, that is, to accumulate the data and process its changes. The new sequence after accumulation is settled as modeling sequence, and the quality of the modeling sequence directly affects the performance of the grey prediction model. Compared with the traditional integer order accumulation generation process, the fractional order accumulation generation process can search the accumulation generation order of the modeling sequence with better quality in a wider range (Wu et al., 2015a).

(II) The time response function of the new model is derived by using the latest value as the initial value, which reflects the timeliness of information. Different from the initial value selection based on the principle of “minimum simulation error”, we follow the idea of sacrificing some simulation accuracy to select the initial value in order to improve the prediction accuracy. According to the “new information priority” principle, the latest data has the greatest impact on the development of the sequence, so the latest data is used as the initial value in this article to ensure that the prediction accuracy is further improved.

(III) The buffer operator constructed by subjective weighting has a greater impact on the rationality of the data. There is no need to use a weighted buffer operator. Hence, the modeling sequence of the new model can be pre-processed by a general buffer operator.

This paper uses a lot of symbols and abbreviations. To improve the readability of the article, the meanings of symbols are

Table 1
Symbols and their meanings.

Index	Symbol	Meaning
1	$S^{(0)}$	An original time sequence
2	$S^{(r)}$	r - fractional order accumulation of sequence $S^{(0)}$
3	$S^{(0)}D$	1-average weakening buffer operator sequence of $S^{(0)}$
4	$\hat{s}^{(r)}(k)$	The simulated value of $s^{(r)}(k)$

listed in Table 1. Similarly, the core abbreviations, corresponding definitions and expressions are listed in Table 2.

The remaining of this paper is organized as follows: In Section 2, we briefly introduce the average weakening buffer operator (AWBO). In Section 3, we propose a new grey prediction model for shale gas output called SGGM(1,1, r), and then deduce the solution of new model and study its properties. In Section 4, we study the modeling condition and error-checking methods for new model. In Section 5, we validate the modeling effect of the new prediction model on China's shale gas output. Based on these findings, we forecast the future shale gas output in China and provide suggestions for future shale gas development. And the conclusions are drawn in Section 6.

To gain a clearer understanding, the structure chart of the article is given as Fig. 1.

2. Data preprocessing method: Grey average weakening buffer operator

The real system is often affected by shock disturbances and led the model loses its effectiveness (Zhou et al., 2020; Zeng et al., 2020a). When the system behavior sequence is distorted by a certain impact, it can no longer correctly reflect the true developing law of the system, and then it is difficult to predict the future changes based on the disturbed sequence. For example, the actual growth rate of shale gas in China is decreasing from 700% to 21% between 2012 and 2018; the average annual increase rate between 2012 and 2016 was about 320%; If we put the growth rate into the mathematical model to forecast the output of shale gas in China at year 2018, the predicted output will reach to 700 Hmcm. However, the actual output is just 108.81 Hmcm, which has big different from the quantitative prediction result. This means that if the prediction model completely depends on the current law of the growth rate of the original sequence, and the lack of qualitative analysis based on the future system development trend, it will cause the prediction results to be invalid.

To eliminate the impact interference of the system behavior sequence, and restore the data as it is, Professor Liu Sifeng proposed a series of grey buffer sequence operators in 1997. The grey average weakening buffer operator is the most common one among the existing buffer operators. It can addresses the contradiction between low-growth system and high-growth modeling results by suppressing the high-growth characteristics of the system.

Definition 1 (Liu, 1997). Given sequence $S^{(0)} = (s^{(0)}(1), s^{(0)}(2), \dots, s^{(0)}(m))$, where $s^{(0)}(k) \geq 0, k = 1, 2, \dots, m$. Let

$$S^{(0)}D = (s^{(0)}(1)d, s^{(0)}(2)d, \dots, s^{(0)}(m)d)$$

where

$$s^{(0)}(k)d = \frac{1}{m-k+1} [s^{(0)}(k) + s^{(0)}(k+1) + \dots + s^{(0)}(m)],$$

$$k = 1, 2, \dots, m$$
(1)

Then D is a weakening operator which is referred to as an average weakening buffer operator (AWBO).

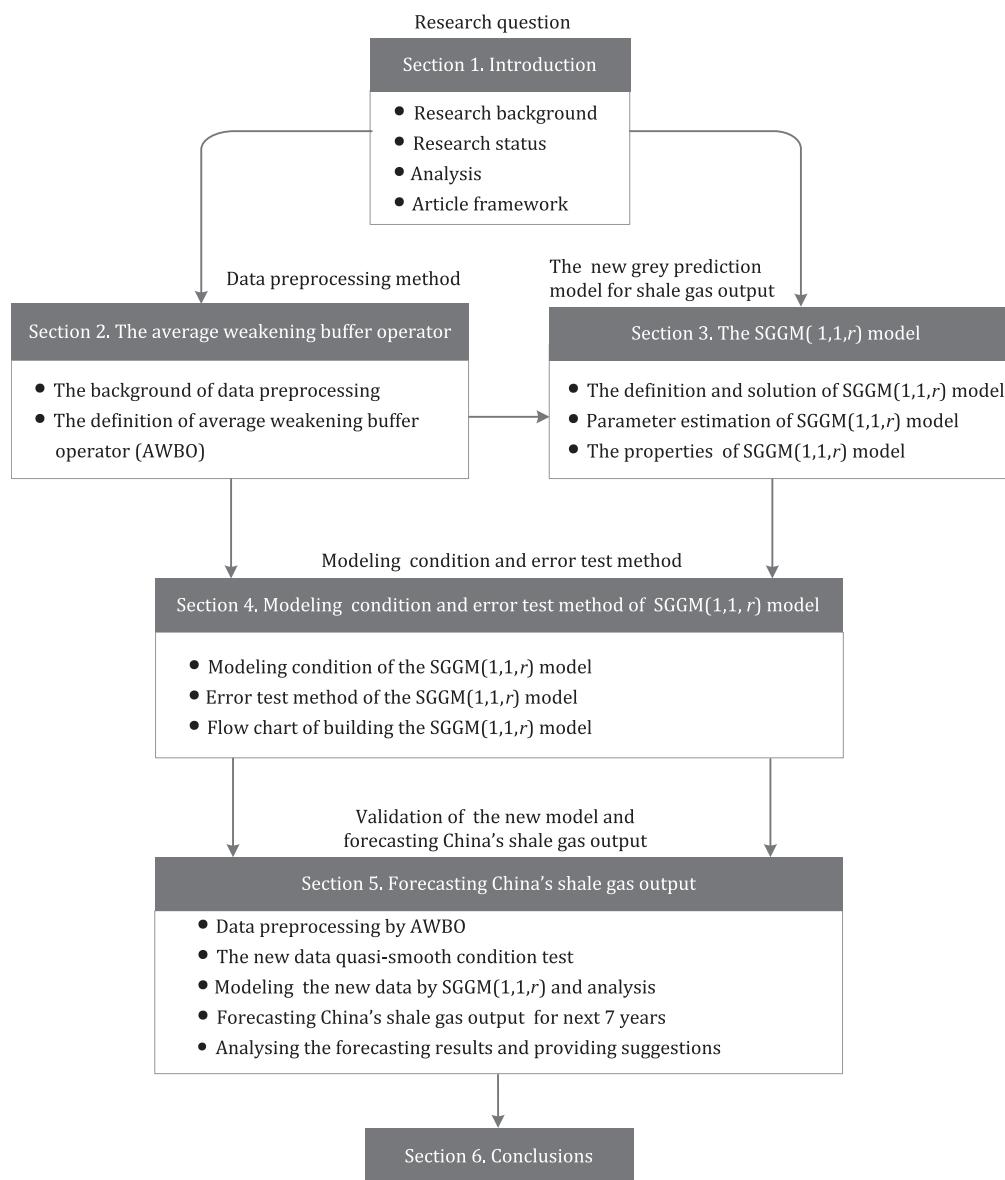


Fig. 1. Structure of this paper.

Table 2
Nomenclature.

Index	Nomenclature	Definition	Expression
1	AWBO	Average weakening buffer operator	$s(k)d = \frac{1}{m-k+1} [s(k) + s(k+1) + \dots + s(m)]$
2	r -FOA	r -order fractional order accumulation	$s^{(r)}(k) = \sum_{i=1}^k \frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)} s^{(0)}(i)$
3	r -IFOA	r -order inverse fractional order accumulation	$s^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} s^{(r)}(k-i)$
4	SGGM(1,1, r)	The basic form of shale gas output grey prediction model	$s^{(r)}(k+1) = \mu_1 s^{(r)}(k) + \mu_2 k + \mu_3$
5	MRSPE	The mean relative simulation percentage error	$\Delta_S(u) = \left \frac{\varepsilon_S(u)}{s^{(0)}(u)} \times 100\% \right $
6	MRPPE	The mean relative prediction percentage error	$\Delta_F(v) = \left \frac{\varepsilon_F(v)}{s^{(0)}(v)} \times 100\% \right $
7	CMRPE	The comprehensive mean relative percentage error	$\Delta = \frac{\Delta_S(1) + \Delta_S(2) + \dots + \Delta_S(m) + \Delta_F(m+1) + \dots + \Delta_F(m+n)}{m+n}$

3. A new grey prediction model for shale gas output

In this section, a new grey prediction model is constructed and its parameter estimation method is proposed. Then the solution of the model is derived with the latest value as the initial value particularly. Finally, properties of the new model is discussed. The detailed modeling process is presented as follows.

3.1. The SGGM(1, 1, r) model

Definition 2. Let sequence $S^{(0)} = (s^{(0)}(1), s^{(0)}(2), \dots, s^{(0)}(m))$ as a raw sequence, $s^{(0)}(k) \geq 0, r \in \mathbb{R}^+, S^{(r)} = (s^{(r)}(1), s^{(r)}(2), \dots, s^{(r)}(m))$ be the r -FAO (Fractional Order Accumulation) of sequence $S^{(0)}$, where

$$s^{(r)}(k) = \sum_{i=1}^k \frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)} s^{(0)}(i), k = 1, 2, \dots, m \quad (2)$$

then when $k = 1, 2, \dots, m$,

$$s^{(r)}(k+1) = \mu_1 s^{(r)}(k) + \mu_2 k + \mu_3 \quad (3)$$

is referred to as the basic form of shale gas output grey prediction model, SGGM(1,1, r) for short.

Definition 3. Let sequence $S^{(r)} = (s^{(r)}(1), s^{(r)}(2), \dots, s^{(r)}(m))$ as a raw sequence, $s^{(r)}(k) \geq 0, r \in \mathbb{R}^+, S^{(0)} = (s^{(0)}(1), s^{(0)}(2), \dots, s^{(0)}(m))$ be the r -IFAO (Inverse Fractional Order Accumulation) of sequence $S^{(r)}$, where

$$s^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} s^{(r)}(k-i), \quad (4)$$

$k = 1, 2, \dots, m$

3.2. The parameters estimation of SGGM(1, 1, r)

We use ordinary least-squares (OLS) method and Cramer's ruler to estimate the parameters μ_1, μ_2 and μ_3 according to the equation of SGGM(1, 1, r).

Let $\hat{s}^{(r)}(k)$ be the simulated value of $s^{(r)}(k)$ and $\hat{\mu}_1, \hat{\mu}_2, \hat{\mu}_3$ are the parametric estimated value of SGGM(1,1, r). According to OLS, the following conditions need to be satisfied when the simulation error is minimal:

$$\begin{aligned} \Delta &= \min \sum_{k=2}^m [s^{(r)}(k) - \hat{s}^{(r)}(k)]^2 \\ &= \min \sum_{k=2}^m [s^{(r)}(k) - \mu_1 s^{(r)}(k-1) - \mu_2 (k-1) - \mu_3]^2 \end{aligned} \quad (5)$$

We minimize Δ with parameters $\hat{\mu}_1, \hat{\mu}_2$ and $\hat{\mu}_3$ to obtain

$$\begin{cases} \frac{\partial \Delta}{\partial \hat{\mu}_1} = -2 \sum_{k=2}^m [s^{(r)}(k) - \hat{\mu}_1 s^{(r)}(k-1) - \hat{\mu}_2 (k-1) - \hat{\mu}_3] s^{(r)}(k-1) \\ \quad \times (k-1) = 0 \\ \frac{\partial \Delta}{\partial \hat{\mu}_2} = -2 \sum_{k=2}^m [s^{(r)}(k) - \hat{\mu}_1 s^{(r)}(k-1) - \hat{\mu}_2 (k-1) - \hat{\mu}_3] \\ \quad \times (k-1) = 0 \\ \frac{\partial \Delta}{\partial \hat{\mu}_3} = -2 \sum_{k=2}^m [s^{(r)}(k) - \hat{\mu}_1 s^{(r)}(k-1) - \hat{\mu}_2 (k-1) - \hat{\mu}_3] = 0 \end{cases} \quad (6)$$

After transposition, we obtain

$$\begin{cases} \hat{\mu}_1 \sum_{k=2}^m s^{(r)}(k-1)^2 + \hat{\mu}_2 \sum_{k=2}^m (k-1) s^{(r)}(k-1) \\ \quad + \hat{\mu}_3 \sum_{k=2}^m s^{(r)}(k-1) = \sum_{k=2}^m [s^{(r)}(k) s^{(r)}(k-1)] \\ \hat{\mu}_1 \sum_{k=2}^m (k-1) s^{(r)}(k-1) + \hat{\mu}_2 \sum_{k=2}^m (k-1)^2 \\ \quad + \hat{\mu}_3 \sum_{k=2}^m (k-1) = \sum_{k=2}^m [(k-1) s^{(r)}(k)] \\ \hat{\mu}_1 \sum_{k=2}^m s^{(r)}(k-1) + \hat{\mu}_2 \sum_{k=2}^m (k-1) + \hat{\mu}_3 (m-1) = \sum_{k=2}^m s^{(r)}(k) \end{cases} \quad (7)$$

In Eq. (7), parameters $\hat{\mu}_1, \hat{\mu}_2$ and $\hat{\mu}_3$ are unknown. According to Cramer's rule, we can calculate these unknown parameters, to obtain

$$D = \begin{vmatrix} \sum_{k=2}^m s^{(r)}(k-1)^2 & \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m s^{(r)}(k-1) \\ \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m (k-1)^2 & \sum_{k=2}^m (k-1) \\ \sum_{k=2}^m s^{(r)}(k-1) & \sum_{k=2}^m (k-1) & m-1 \end{vmatrix}$$

$$D_1 = \begin{vmatrix} \sum_{k=2}^m [s^{(r)}(k) s^{(r)}(k-1)] & \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m s^{(r)}(k-1) \\ \sum_{k=2}^m (k-1) s^{(r)}(k) & \sum_{k=2}^m (k-1)^2 & \sum_{k=2}^m (k-1) \\ \sum_{k=2}^m s^{(r)}(k) & \sum_{k=2}^m (k-1) & m-1 \end{vmatrix}$$

$$D_2 = \begin{vmatrix} \sum_{k=2}^m s^{(r)}(k-1)^2 & \sum_{k=2}^m [s^{(r)}(k) s^{(r)}(k-1)] & \sum_{k=2}^m s^{(r)}(k-1) \\ \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m (k-1) s^{(r)}(k) & \sum_{k=2}^m (k-1) \\ \sum_{k=2}^m s^{(r)}(k-1) & \sum_{k=2}^m s^{(r)}(k) & m-1 \end{vmatrix}$$

$$D_3 = \begin{vmatrix} \sum_{k=2}^m s^{(r)}(k-1)^2 & \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m [s^{(r)}(k) s^{(r)}(k-1)] \\ \sum_{k=2}^m (k-1) s^{(r)}(k-1) & \sum_{k=2}^m (k-1)^2 & \sum_{k=2}^m (k-1) s^{(r)}(k) \\ \sum_{k=2}^m s^{(r)}(k-1) & \sum_{k=2}^m (k-1) & \sum_{k=2}^m s^{(r)}(k) \end{vmatrix}$$

In light of Cramer's rule, parameters $\hat{\mu}_1, \hat{\mu}_2$ and $\hat{\mu}_3$ can be computed as follows:

$$\hat{\mu}_1 = \frac{D_1}{D}, \quad \hat{\mu}_2 = \frac{D_2}{D}, \quad \hat{\mu}_3 = \frac{D_3}{D}$$

3.3. The solution of SGGM(1,1,r)

In this subsection, the latest value $s^{(r)}(m)$ is set as initial value which is used to derive the solution of SGGM(1,1, r).

Theorem 1. The SGGM(1,1, r) model is defined as Definition 2, then

(i) The time response function of the SGGM(1,1, r) is as follow:

$$s^{(r)}(k) = \frac{s^{(r)}(m)}{\mu_1^{m-k}} + \frac{\mu_3(1 - \mu_1^{k-m})}{1 - \mu_1} \swarrow \nearrow + \frac{k\mu_2(1 - \mu_1) - m\mu_2(1 - \mu_1)\mu_1^{k-m} - \mu_2(1 - \mu_1^{k-m})}{(1 - \mu_1)^2},$$

$$k = 1, 2, \dots \quad (8)$$

(ii) The final restored expression of $s^{(0)}(k)$ is as follow:

$$\hat{s}^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} \times \left(\frac{s^{(r)}(m)}{\mu_1^{m-k}} + \frac{\mu_3(1 - \mu_1^{k-m})}{1 - \mu_1} \swarrow \nearrow + \frac{k\mu_2(1 - \mu_1) - m\mu_2(1 - \mu_1)\mu_1^{k-m} - \mu_2(1 - \mu_1^{k-m})}{(1 - \mu_1)^2} \right),$$

$$k = 1, 2, \dots \quad (9)$$

Proof. (i) According Definition 2, the simulation process is as follows:

when $k = m - 1$, we can get

$$s^{(r)}(m) = \mu_1 s^{(r)}(m-1) + \mu_2(m-1) + \mu_3 \quad (10)$$

After transposition, we obtain

$$s^{(r)}(m-1) = \frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3}{\mu_1} \quad (11)$$

When $k = m - 2$, we can get

$$s^{(r)}(m-1) = \mu_1 s^{(r)}(m-2) + \mu_2(m-2) + \mu_3 \quad (12)$$

After transposition, we obtain

$$s^{(r)}(m-2) = \frac{s^{(r)}(m-1) - \mu_2(m-2) - \mu_3}{\mu_1} \quad (13)$$

Substituting Eq. (11) into Eq. (13), we can get

$$s^{(r)}(m-2) = \frac{\frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3}{\mu_1} - \mu_2(m-2) - \mu_3}{\mu_1} \quad (14)$$

After transposition, we obtain

$$s^{(r)}(m-2) = \frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3 - \mu_1\mu_2(m-2) - \mu_1\mu_3}{\mu_1^2} \quad (15)$$

When $k = m - 3$, we can get

$$s^{(r)}(m-2) = \mu_1 s^{(r)}(m-3) + \mu_2(m-3) + \mu_3 \quad (16)$$

After transposition, we obtain

$$s^{(r)}(m-3) = \frac{s^{(r)}(m-2) - \mu_2(m-3) - \mu_3}{\mu_1} \quad (17)$$

Substituting Eq. (15) into Eq. (17), we can get

$$s^{(r)}(m-3) = \frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3 - \mu_1\mu_2(m-2) - \mu_1\mu_3}{\mu_1^3} - \frac{\mu_2(m-3) + \mu_3}{\mu_1} \quad (18)$$

After transposition, we obtain

$$s^{(r)}(m-3) = \frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3 - \mu_1\mu_2(m-2) - \mu_1\mu_3}{\mu_1^3} \swarrow \nearrow - \frac{\mu_1^2(\mu_2(m-3) + \mu_3)}{\mu_1^3} \quad (19)$$

⋮

When $k = m - t$, we can get

$$s^{(r)}(m-t) = \frac{s^{(r)}(m) - \mu_2(m-1) - \mu_3 - \mu_1\mu_2(m-2) - \mu_1\mu_3}{\mu_1^t} \swarrow \nearrow - \frac{\mu_1^2\mu_2(m-3) + \mu_1^2\mu_3 + \dots + \mu_1^{t-1}\mu_2(m-t) + \mu_1^{t-1}\mu_3}{\mu_1^t} \quad (20)$$

After transposition, we obtain

$$s^{(r)}(m-t) = \frac{s^{(r)}(m)}{\mu_1^t} - \frac{\mu_3(1 - \mu_1^t)}{\mu_1^t(1 - \mu_1)} + \frac{\mu_2\mu_1(\mu_1^{-t} - \mu_1^{-1})}{(1 - \mu_1)^2} \swarrow \nearrow + \frac{\mu_2(m-t)(1 - \mu_1) - (1 - \mu_1)\mu_2(m-1)\mu_1^{-t}}{(1 - \mu_1)^2} \quad (21)$$

Let $m - k = t$, feed t into Eq. (21) and can obtain the time response function of SGGM(1,1, r), which is

$$s^{(r)}(k) = \frac{s^{(r)}(m)}{\mu_1^{m-k}} + \frac{\mu_3(1 - \mu_1^{k-m})}{1 - \mu_1} \swarrow \nearrow + \frac{k\mu_2(1 - \mu_1) - m\mu_2(1 - \mu_1)\mu_1^{k-m} - \mu_2(1 - \mu_1^{k-m})}{(1 - \mu_1)^2} \quad (22)$$

(ii) According Definition 2, the prediction process is as follows

When $k = m + 1$, we can get

$$s^{(r)}(m+1) = \mu_1 s^{(r)}(m) + \mu_2 m + \mu_3 \quad (23)$$

When $k = m + 2$, we can get

$$s^{(r)}(m+2) = \mu_1 s^{(r)}(m+1) + \mu_2(m+1) + \mu_3 \quad (24)$$

Substituting Eq. (23) into Eq. (24), we can get

$$s^{(r)}(m+2) = \mu_1^2 s^{(r)}(m) + \mu_1\mu_2 m + \mu_1\mu_3 + \mu_2(m+1) + \mu_3 \quad (25)$$

When $k = m + 3$, we can get

$$s^{(r)}(m+3) = \mu_1 s^{(r)}(m+2) + \mu_2(m+2) + \mu_3 \quad (26)$$

Substituting Eq. (25) into Eq. (26), we can get

$$s^{(r)}(m+3) = \mu_1^3 s^{(r)}(m) + \mu_1^2\mu_2 m + \mu_1^2\mu_3 + \mu_1\mu_2(m+1) + \mu_1\mu_3 + \mu_2(m+2) + \mu_3 \quad (27)$$

⋮

When $k = m + t$, we can get

$$s^{(r)}(m+t) = \mu_1^t s^{(r)}(m) + \mu_1^{t-1}\mu_2 m + \mu_1^{t-2}\mu_2(m+1) + \dots + \mu_1\mu_2(m+t-2) \swarrow \nearrow + \mu_2(m+t-1) + \mu_1^{t-1}\mu_3 + \mu_1^{t-2}\mu_3 + \dots + \mu_1\mu_3 + \mu_3 \quad (28)$$

After transposition, we obtain

$$\begin{aligned} s^{(r)}(m+t) &= \mu_1^t s^{(r)}(m) + \frac{\mu_3(1-\mu_1^t)}{1-\mu_1} + \frac{(1-\mu_1)\mu_2(m+t)}{(1-\mu_1)^2} \swarrow \\ &\nearrow - \frac{(1-\mu_1)\mu_1^t\mu_2m + \mu_2(1-\mu_1^t)}{(1-\mu_1)^2} \end{aligned} \quad (29)$$

Let $k-m=t$, feed t into Eq. (29) and can obtain the time response function of SGGM(1,1, r), which is

$$\begin{aligned} s^{(r)}(k) &= \frac{s^{(r)}(m)}{\mu_1^{m-k}} + \frac{\mu_3(1-\mu_1^{k-m})}{1-\mu_1} \swarrow \\ &\nearrow + \frac{k\mu_2(1-\mu_1) - m\mu_2(1-\mu_1)\mu_1^{k-m} - \mu_2(1-\mu_1^{k-m})}{(1-\mu_1)^2} \end{aligned} \quad (30)$$

According to Definition 3, the final restored expression of $s^{(r)}(k)$ can be calculated as follows:

$$\hat{s}^{(0)}(k) = \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} s^{(r)}(k) \quad (31)$$

Then substituting Eq. (30) into Eq. (31), we obtain

$$\begin{aligned} \hat{s}^{(0)}(k) &= \sum_{i=0}^{k-1} (-1)^i \frac{\Gamma(r+1)}{\Gamma(i+1)\Gamma(r-i+1)} \\ &\times \left(\frac{s^{(r)}(m)}{\mu_1^{m-k}} + \frac{\mu_3(1-\mu_1^{k-m})}{1-\mu_1} \swarrow \right. \\ &\nearrow \left. + \frac{k\mu_2(1-\mu_1) - m\mu_2(1-\mu_1)\mu_1^{k-m} - \mu_2(1-\mu_1^{k-m})}{(1-\mu_1)^2} \right) \end{aligned} \quad (32)$$

In Eq. (32), $\hat{s}^{(0)}(k)$ is called the restored expression of $S^{(0)}$, which also called the solution of SGGM(1,1, r), where $k=1, 2, \dots$

3.4. The properties of SGGM(1,1, r)

Theorem 2. When $r=1$, the proposed SGGM(1,1, r) model can simulate the following sequences without errors.

(i) A homogeneous exponential sequence

$s = (s^{(0)}(1), s^{(0)}(2), \dots, s^{(0)}(m))$, where $s^{(0)}(t) = aq^k$, $\alpha q \neq 0$ and $k=1, 2, \dots, m$.

(ii) A non-homogeneous exponential sequence

$S = (s^{(0)}(1), s^{(0)}(2), \dots, s^{(0)}(m))$, where $s^{(0)}(t) = \beta q^k + \varphi$, $\beta\varphi q \neq 0$ and $k=1, 2, \dots, m$.

The proof is omitted here.

4. The modeling condition and error checking method of SGGM(1,1, r)

4.1. The modeling condition of SGGM(1,1, r)

The modeling condition testing is a necessary process to establish a prediction model, which enhances the rigor of model. A model can only be used for prediction when the modeling conditions are satisfied. In grey system theory, the quasi-exponential law is usually used as a test method for grey prediction model.

Definition 4. Let $S = (s(1), s(2), \dots, s(m))$, where $s(k) \geq 0$ for $k=1, 2, \dots, m$, then the following is named as the smoothness ratio of sequence:

$$\rho(k) = \frac{s(k)}{\sum_{i=1}^{k-1} s(i)}, \quad k=2, 3, \dots, m$$

The concept of smoothness ratio reflects the smoothness of a sequence. Obviously the smoother the sequence the smaller the smoothing rate is.

Definition 5. If a sequence $S = (s(1), s(2), \dots, s(m))$, where $s(k) \geq 0$ for $k=1, 2, \dots, m$ satisfies the following conditions, then S is referred to as a quasi-smooth sequence.

- (i) $\frac{\rho(k+1)}{\rho(k)} < 1$, $k=2, 3, \dots, m-1$;
- (ii) $\rho(k) = [0, \varepsilon]$, $k=3, 4, \dots, m$;
- (iii) $\varepsilon < 0.8$.

The quasi-smooth condition of a sequence is the basis for judging whether the SGGM(1,1, r) model can be established.

4.2. The error checking method of SGGM(1,1, r)

In practice, it may never know what a real system model is, but a “relatively” accurate model can be used to describe the real system. Generally speaking, a good model often has properties such as goodness of fit, predictive power, and so on. In order to check the error of the SGGM(1,1, r) model, the following error checking methods are introduced:

Definition 6. Let $S^{(0)} = (s(1), s(2), \dots, s(m), s(m+1), \dots, s(m+n))$ as a raw sequence. Using the first m elements of $S^{(0)}$ build the SGGM(1,1, r) model; the simulation sequence is $\hat{S}^{(0)}$, which is given as follows

$$\hat{S}^{(0)} = (\hat{s}^{(0)}(1), \hat{s}^{(0)}(2), \dots, \hat{s}^{(0)}(m))$$

Using the last m elements of $S^{(0)}$ build the SGGM(1,1, r) model; the prediction sequence is $\hat{F}^{(0)}$, which is given as follows

$$\hat{F}^{(0)} = (\hat{s}^{(0)}(m+1), \hat{s}^{(0)}(m+2), \dots, \hat{s}^{(0)}(m+n))$$

The error of simulation sequence and prediction sequence are marked as ε_S and ε_F respectively, which are given as follows

$$\varepsilon_S = (\varepsilon_S(1), \varepsilon_S(2), \dots, \varepsilon_S(m)),$$

$$\varepsilon_F = (\varepsilon_F(m+1), \varepsilon_F(m+2), \dots, \varepsilon_F(m+n))$$

where

$$\varepsilon_S(u) = s^{(0)}(u) - \hat{s}^{(0)}(u), \quad u=1, 2, \dots, m$$

$$\varepsilon_F(v) = s^{(0)}(v) - \hat{s}^{(0)}(v), \quad v=m+1, m+2, \dots, m+n$$

The relative simulation percentage error of $\hat{S}^{(0)}$ is marked as Δ_S . That is

$$\Delta_S = (\Delta_S(1), \Delta_S(2), \dots, \Delta_S(m))$$

where

$$\Delta_S(u) = \left| \frac{\varepsilon_S(u)}{s^{(0)}(u)} \times 100\% \right|, \quad u=1, 2, \dots, m$$

The mean relative simulation percentage error (MRSPE) of $\hat{S}^{(0)}$ is marked as $\bar{\Delta}_S$. That is

$$\bar{\Delta}_S = \frac{1}{m} \sum_{u=1}^m \Delta_S(u)$$

The relative prediction percentage error of $\hat{F}^{(0)}$ is marked as Δ_F . That is

$$\Delta_F = (\Delta_F(m+1), \Delta_F(m+2), \dots, \Delta_F(m+n))$$

Table 3

Output of shale gas in China from 2012 to 2018. (Unit:Hundred million cubic meters).
Source: Data sources (http://www.gov.cn/xinwen/2019-07/16/content_5410035.htm).

Year	2012	2013	2014	2015	2016	2017	2018
Output	0.25	2	13	44.71	78.82	89.95	108.81

where

$$\Delta_F(v) = \left| \frac{\varepsilon_F(v)}{s^{(0)}(v)} \times 100\% \right|, \quad v = m+1, m+2, \dots, m+n$$

The mean relative prediction percentage error (MRPPE) of $\hat{F}^{(0)}$ is marked as $\bar{\Delta}_F$. That is

$$\bar{\Delta}_F = \frac{1}{n} \sum_{v=m+1}^{m+n} \Delta_F(v)$$

The comprehensive mean relative percentage error (CMRPE) of $S^{(0)}$ is marked as Δ . That is

$$\Delta = \frac{\Delta_S(1) + \Delta_S(2) + \dots + \Delta_S(m) + \Delta_F(m+1) + \dots + \Delta_F(m+n)}{m+n}$$

For given threshold value α, β, ω , when $\bar{\Delta}_S < \alpha, \bar{\Delta}_F < \beta$ and $\Delta < \omega$ is satisfied, the grey model is said to be error-satisfactory.

4.3. The modeling flow chart for SGGM(1,1,r)

According to the SGGM(1,1,r) modeling process, the modeling flow chart is shown in Fig. 2.

5. Forecasting China's shale gas output

5.1. Data preprocessing

The precondition for forecasting is that the system will develop in accordance with the existing laws, and on this basis, the prediction of system development trend can be realized. However, the reality system may not move forward in full accordance with the existing laws. It is necessary to use data preprocessing methods to add future trends of the system to existing models in order to achieve more accurate predictions in the future. Therefore, before modeling China's shale gas output, the raw data needs to be analyzed and preprocessed as follows.

(i) Data collection: China's shale gas exploration history is relatively short, and the shale gas output records began in 2012. We collected the shale gas output data from 2012 to 2018 published by Chinese government website, as shown in Table 3.

(ii) Data analysis: we draw a scatter of China's shale gas output based on the data in Table 1, and the scatter is shown in Fig. 3.

It can be seen from Fig. 3. that China's shale gas output grows monotonously at different growth rates in each periods: the shale gas output increased sharply from 2012 to 2016, and from 2016 to 2018, shale gas output growth slowly. It indicates that the output is unlikely to maintain a high-speed development trend in the future.

(iii) Data preprocessing using average weakening buffer operator: from the above analysis results, China's shale gas output has grown rapidly between 2012 and 2016, which contradicts the qualitative analysis. To this end, we use the average weakening buffer operator to process the raw sequence from 2012 to 2016.

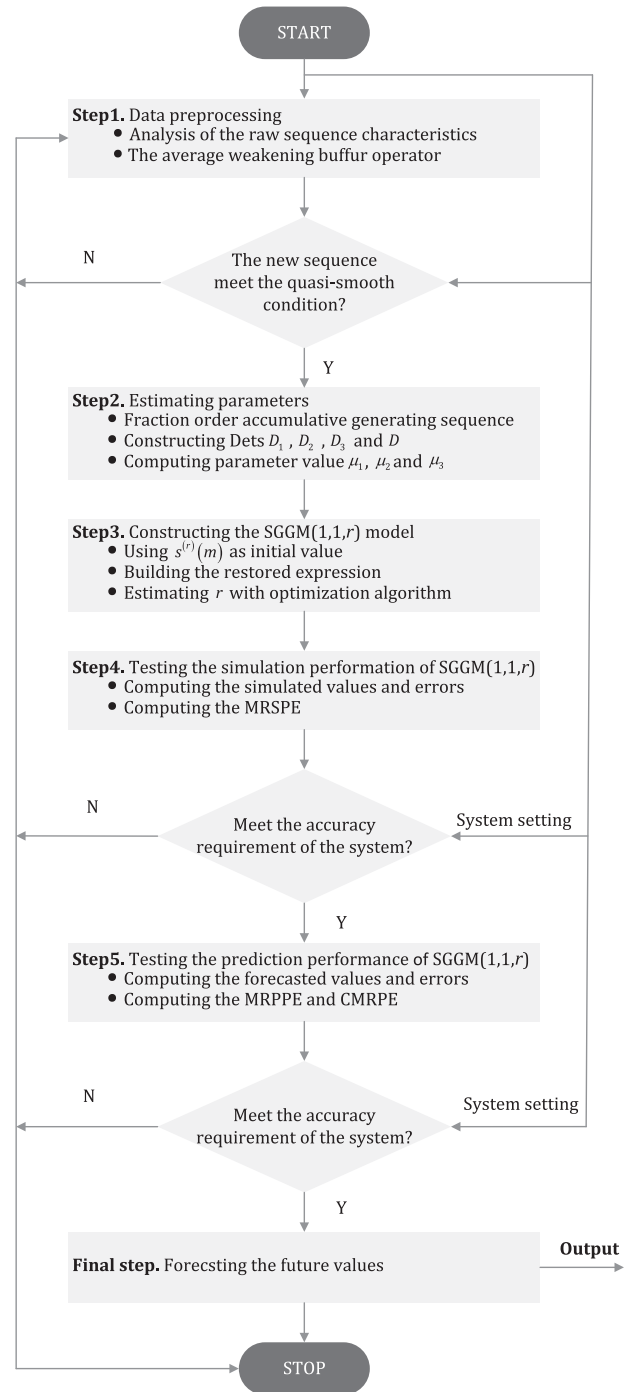


Fig. 2. Flowchart for the SGGM(1,1,r) model.

We know from Table 1 that

$$S^{(0)} = (s^{(0)}(1), s^{(0)}(2), s^{(0)}(3), s^{(0)}(4), s^{(0)}(5), s^{(0)}(6), s^{(0)}(7)) \\ = (0.25, 2, 13, 44.71, 78.82, 89.95, 108.81)$$

According to Definition 1,

$$S^{(0)}D = (s^{(0)}d(1), s^{(0)}(2)d, s^{(0)}(3)d, s^{(0)}(4)d, s^{(0)}(5)d, \\ s^{(0)}(6)d, s^{(0)}(7)d) \\ = (27.76, 34.63, 45.51, 61.77, 78.82, 89.95, 108.81)$$

The scatter diagrams of raw sequence $S^{(0)}$ and preprocessed sequence $S^{(0)}D$ is shown in Fig. 4.

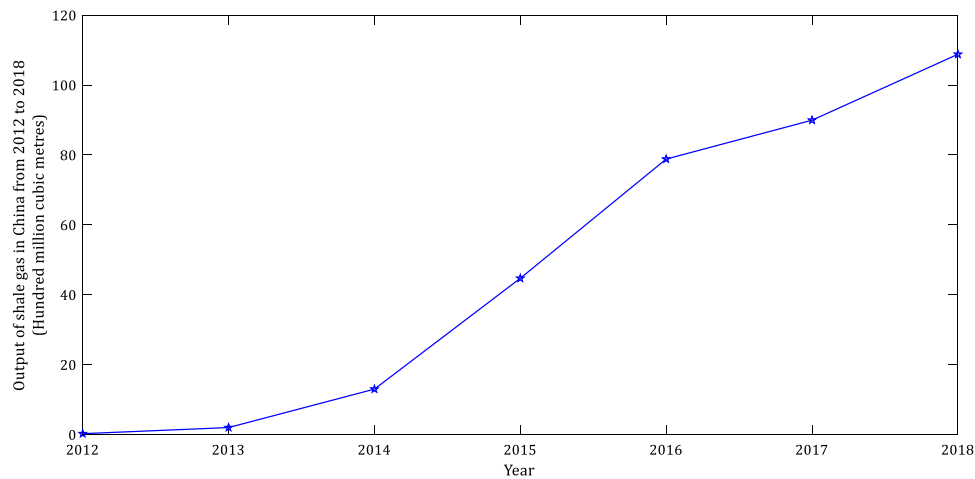


Fig. 3. The scatter of China's shale gas output.

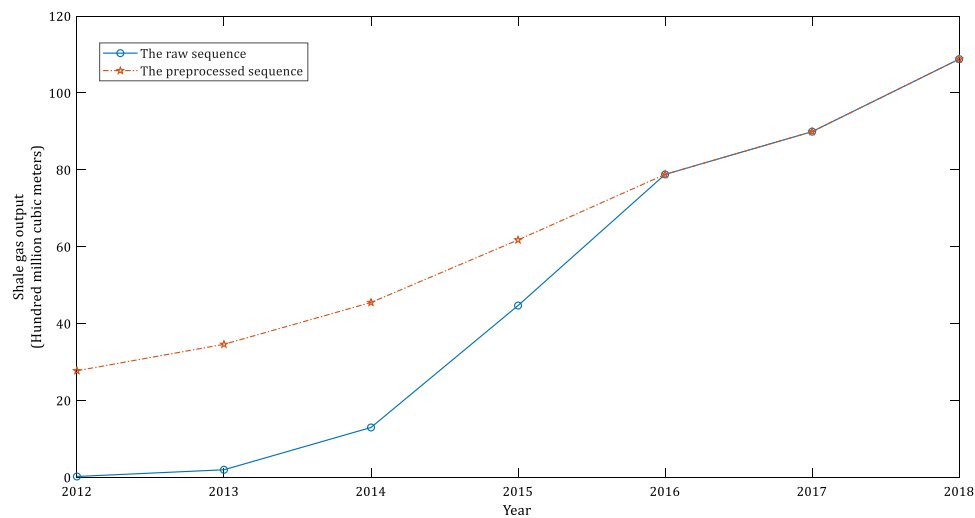


Fig. 4. The scatter diagrams of the raw sequence $S^{(0)}$ and the preprocessed sequence $S^{(0)D}$.

Table 4

The smoothness ratios and quasi-smooth conditions of sequence SD .

Smoothness ratio	$\rho(2) = 1.247$	$\rho(3) = 0.729$	$\rho(4) = 0.572$	$\rho(5) = 0.465$	$\rho(6) = 0.362$
Quasi-smooth condition	–	$\frac{\rho(3)}{\rho(2)} = 0.585$	$\frac{\rho(4)}{\rho(3)} = 0.785$	$\frac{\rho(5)}{\rho(4)} = 0.811$	$\frac{\rho(6)}{\rho(5)} = 0.779$

5.2. Quasi-smooth condition test

A sequence needs to be tested for quasi-smooth condition before modeling. Therefore, we perform a quasi-smooth test on sequence SD before establishing the $SGGM(1,1, r)$ model.

From Definitions 4 and 5, the Smoothness ratios and quasi-smooth conditions of sequence SD are obtained as shown in Table 4.

As shown in Table 4, when $k = 3, 4, 5, 6$, the Smoothness ratios are all less than 0.8; when $k = 2, 3, \dots, 5$, the quasi-smooth conditions are all less than 1. According to Definition 5, the sequence SD satisfies the quasi-smoothness conditions, and can be used to establish the $SGGM(1,1, r)$ model.

5.3. Modeling by $SGGM(1,1, r)$ model

In the calculating processing below, we choose the China's shale gas output value from 2012 to 2016 as training set, and

Table 5

The parameters of $SGGM(1,1, r)$.

Parameter	r	μ_1	μ_2	μ_3
Value	0.026623	0.674471	7.512238	8.812008

the China's shale gas output value in 2017 and 2018 as test set, and utilize Particle Swarm optimization (PSO) to estimate r of $SGGM(1,1, r)$ model. The unknown parameters of $SGGM(1,1, r)$ are presented in Table 5. The simulation and prediction value, MRSPE, MRPPE and CMRPE of $SGGM(1,1, r)$ and $UGM(1,1)$ are presented in Table 6.

5.4. Comparing and analysis

The quantitative evaluations are given in Table 6, we can learn that the $SGGM(1,1, r)$ model improves the $UGM(1,1)$ model with and 84.34%, 68.96% and 75.60% reductions in the MRSPE,

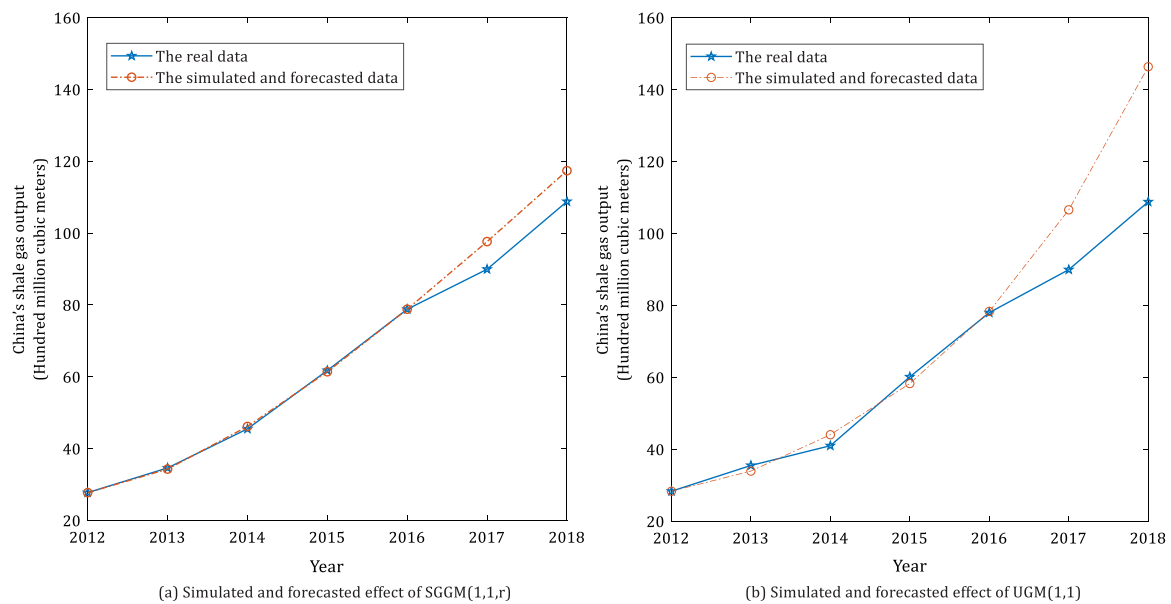


Fig. 5. The scatter diagrams of simulation and prediction value of two models.

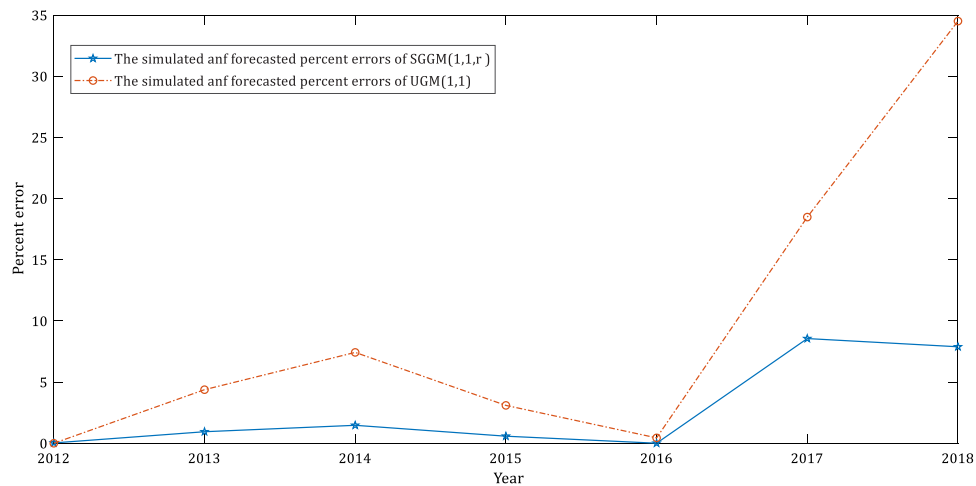


Fig. 6. The scatter diagrams of simulation and prediction percent error of SGGM(1,1, r) and UGM(1,1).

Table 6

Results of the value by SGGM(1,1, r) and UGM(1,1). (Unit:Hundred million cubic meters).

Year	No	SGGM(1,1, r)			UGM(1,1) (Zeng et al., 2018)		
		Processed value	Simulation value	Relative error (%)	Processed value	Simulation value	Relative error (%)
2012	1	27.76	27.752	0.014	28.36	28.360 ^a	0 ^a
2013	2	34.63	34.303	0.944	35.52	33.964	4.381
2014	3	45.51	46.179	1.468	41.02	44.067	7.428
2015	4	61.77	61.413	0.578	60.16	58.297	3.097
2016	5	78.82	78.823	0.004	78.00	78.344	0.441
		Actual value	Prediction value	Relative error (%)	Actual value	Prediction value	Relative error (%)
2017	6	89.95	97.650	8.559	89.95	106.581	18.489
2018	7	108.81	117.393	7.888	108.81	146.358	34.508
MRSPE (2012–2016)			0.601			3.837	
MRPPE (2017–2018)			8.224			26.499	
CMRPE (2012–2018)			2.779			11.391	

^aThe data here is supplementary data, which is convenient for comparison.

MRPPE and CMRPE respectively. To vividly show models performance, two perspectives are considered: one is fitting effect, and the other is modeling error. They are shown in Figs. 5 and 6 respectively.

Compared with Fig. 5(a) and (b), the simulated values of SGGM(1,1, r) are nearly completely fit the processed value, and is more accurate than the simulated values of UGM(1,1). And the forecasted values of SGGM(1,1, r) tends to be closer to the real

Table 7

Prediction values by the SGGM(1,1, r) model for China's shale gas output. (Unit:Hundred million cubic meters).

Year	2019	2020	2021	2022	2023	2024	2025
Value	123.0247	137.9089	152.8928	167.8652	182.8062	197.7142	212.5912

value, while the forecasted values of UGM(1,1) trends to deviate from the real value. Fig. 6 illustrates that the modeling errors of UGM(1,1) is always bigger than that of SGGM(1,1, r). In summary, it apparently indicates that the SGGM(1,1, r) model is superior to the UGM(1,1) model for forecasting China's shale gas output.

We also use classic grey prediction models to predict and simulate the China's shale gas output. The experimental results show that the simulation error of the classic GM(1,1) model (Deng, 1989) is as high as 735.62% and the prediction error is up to 460.4%; the simulation error of the classic discrete grey prediction model DGM(1,1) model (Xie and Liu, 2005) is as high as 74.29% and the prediction error is 663.38% higher. Obviously, classic grey prediction models have no reference value for the prediction of China's shale gas output.

5.5. Forecasting the future output from 2019 to 2025

Because of its outstanding performance, the SGGM(1,1, r) model is employed to predict the China's shale gas output in the next 7 years, and the prediction results are shown in Table 7.

In the absence of major technological breakthroughs and strong policy guidance, there will be no huge changes in the shale gas exploration system, so the annual growth rate of shale gas production will be relatively stable. It can be seen from Table 7 that China's shale gas production will maintain a relatively stable growth rate at the current low growth rate in the next few years. It indicates that the prediction results are reasonable and consistent with the low development level of the shale gas exploration system.

5.6. Suggestions for China's shale gas output

The China's shale gas development plan (2016–2020) expected to produce 300 Hmcm of shale gas in 2020. However, The prediction results show the output will reach to about 140 Hmcm by 2020, it indicates only 45.97% of the planned shale gas output can be completed in 2020. In this case, it is difficult to reverse China's excessive dependence on coal energy structure and reduce its dependence on foreign energy at the current development level. In order to promote the development of shale gas in China, the main measures are to break through the technical bottleneck of shale gas exploration and provide appropriate shale gas policy guidance. After that, China's shale gas output can meet the planning requirements of energy policies.

Firstly, it should break through the core technology of shale gas development and take into account the research and development of supporting technologies for shale gas development. China's government departments should increase investment and attention in shale gas research, and encourage scientific researchers to carry out relevant scientific research through special programs to provide a strong guarantee for shale gas development technology. It is worth noting that shale gas has obvious geological particularity. Due to the different geological characteristics of various countries, mature shale gas development technology cannot be directly applied abroad. Therefore, researchers need to study a series of issues such as shale gas production conditions and shale gas properties in China to form a shale gas theory that conforms to China's geological characteristics. Secondly, appropriate policy should be making as

the guarantee and driving force for the development of shale gas industry. China's government departments should eliminate barriers for shale gas to enter the market, enhancing the competitiveness of the oil and gas market, and formulate corresponding regulations for oil and gas companies to monitor their market behavior and restrict monopolistic behavior, maintaining a healthy market competition environment. In addition, for long-term sustainable development of shale gas resources, It is necessary to ensure the “green” development of shale gas. That is to take into account environmental protection during the development of shale gas, minimize waste of resources and environmental pollution, and build the clean development of shale gas.

6. Conclusions

The output of shale gas plays an important role in making energy policies, especially for China whose energy structure is in transition from high-carbon energy to clean energy. This study proposed a new shale gas output grey prediction model, named the SGGM(1,1, r) model. The experimental results and quantitative analysis conclusions demonstrated that the new model has well performance and is suitable for forecasting China's shale gas output.

The existing grey shale gas output prediction model caused inadequate initial value, stiff accumulative generation order and inappropriate data preprocessing method, which led to an unsatisfied prediction result. To this end, the SGGM(1,1, r) model was constructed to overcome the above shortcoming. The new model was design by consideration “new information priority” principle and fraction accumulative generation operation, and its time response function was derived by using the latest value as the initial value. Subsequently, the new model was applied to simulate and forecast China's shale gas output incorporating grey average weakening buffer operator. Comparing the experimental results of the new model with that of the existing model, the former was significantly better than the latter. Finally, the new model was used to predict the shale gas output during the period from 2019 to 2025, and some advice were given for developing China's shale gas output.

This research, however, is subject to the limitation of the high uncertainty of China's shale gas system, which limits the prediction ability of grey prediction model. In grey system theory, the grey prediction model is modeled by the grey system behavior sequence to achieve the purpose of prediction; theoretically, by increasing the system whitening information, the uncertainty of the system can be reduced, and the prediction accuracy of the grey model can be further improved (Zeng et al., 2020b). In the future, we will conduct further research on the shale gas system, extract the whitening information of China's shale gas system, and set more model parameters based on the whitening information to enhance the prediction ability of the grey prediction model, which is of great significance for formulating energy policies.

CRedit authorship contribution statement

Bo Zeng: Conceptualization, Resources, Supervision, Project administration, Funding acquisition. **Meng Zhou:** Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing - original draft, Writing - review & editing. **Xi-anzhou Liu:** Writing - original draft, Visualization. **Zhiwei Zhang:** Writing - original draft, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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