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Application of a New Information Priority Accumulated Grey Model with Simpson to Forecast Carbon Dioxide Emission

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Authors' contributions

This work was carried out in collaboration among all authors. Author XX designed the study, performed the mathematical analysis, wrote the protocol and wrote the first draft of the manuscript. Authors XX and YC managed the analyses of the study. Author SX managed the literature searches. All authors read and approved the final manuscript.

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Abstract

Climate warming is a hot topic of common concern all over the world and it has had a significant impact on climate, oceans and human life. The increase in the concentration of carbon dioxide in the atmosphere has become a significant factor in climate warming. In recent years, the concentration of carbon dioxide in the atmosphere has been mostly anthropogenic emissions. Accurate forecasting of carbon dioxide emissions will effectively propose solutions to the problem of global warming and then improve the environment in which we live. In our work, first of all, we use the new information priority accumulation method to optimize the weight of the new information in the prediction. Then we use the numerical integration method to optimize the background value of the grey model to achieve more accurate forecast. Application case results show that our proposed model is superior to other grey models in predicting carbon dioxide emission in India and Bangladesh.

Keywords: Carbon dioxide emission; grey system model; new information priority; Simpson.

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1 Introduction

The issue of climate warming has received widespread attention in the world, and the increase in greenhouse gas concentrations in the atmosphere is the leading cause of climate change **Error! Reference source not found.**. In which, carbon dioxide is the most critical single greenhouse gas. Due to the emission of carbon dioxide from human activities, such as energy consumption, deforestation, cement production and other activities [1] , the concentration of carbon dioxide in the atmosphere rises accordingly, and the problem of climate warming caused by carbon dioxide has reached a point that cannot be ignored 0. If greenhouse gas emissions are not significantly reduced, the climate will change considerably in the future 0. The harm caused by climate change is enough to affect the world, such as: increasing the probability of extreme weather, reducing people's access to resources 0, providing favorable conditions for disease transmission [10] and affecting polar ice cores 0.

As early as 1995, some scholars studied the impact of greenhouse gas emissions on climate change in the Asia-Pacific region and predicted greenhouse gas emissions 0. According to BP statistics, until 2018, the Asia-Pacific region's carbon dioxide emissions accounted for 49.4% of the world's total, while India's second-largest share in the Asia-Pacific region accounted for 7.3% globally. Therefore, studying carbon dioxide emissions is a top priority for climate warming, and it is urgent to propose an accurate prediction model of carbon dioxide emissions.

Grey system theory is a control theory of systems with incomplete or uncertain information, which has attracted the attention of many scholars at home and abroad since Professor Deng proposed it in [13]. And a great deal of outstanding work has been conducted to make significant progress in theory and application. Xie et al. 0designed a discrete grey prediction model, which solved the prediction stability of the classical grey model to some extent. Chen et al. 0proposed a new grey model by using the Bernoulli differential equation and named it nonlinear grey Bernoulli model. Cui et al. 0proposed a new grey model by replacing the traditional grey function with time linear function and obtained more satisfactory results. Then Truong d.q and others 0proposed the SAGM (1,1) model with higher prediction accuracy. Wu et al. 0first extended the grey model to fractional accumulation and designed a new grey model with strong innovation. In terms of the background value of the grey model, Wang et al. 0first optimized the grey model from the perspective of improving the whitened value of the grey derivative. Zeng et al. 0extended the idea of background value reconstruction and established a new multivariate grey model. After that, Wu et al. 0 put forward the way of adjusting the information weight to improve the prediction accuracy, which provides the basis for the work of this paper. In a nutshell, improving the prediction accuracy of the model is the top priority of the grey model improvement.

In summary, carbon dioxide emissions not only affect global climate change, but are also critical to a country's ecological environment, energy consumption, economic growth, and human life safety. And accurately realizing the prediction of carbon dioxide emissions will help mitigate and overcome these potential threats. On the other hand, the traditional grey model has many defects. Although the above work has improved the prediction accuracy of the model to some extent, especially the improvement of the model background value, it still ignores the important role of new information priority.

In this paper, the grey model is improved by changing the weight of new information and old information in the original sequence, and the prediction accuracy is further improved by combining the numerical integration formula. The new model proposed in this paper is applied to the prediction of carbon dioxide emissions in India and Bangladesh in the Asia Pacific region. By comparing the evaluation indexes of several models, the prediction accuracy of this model is higher than that of other traditional models. This model was used to predict the carbon dioxide emissions of India and Bangladesh in the Asia Pacific region. The results of the model proposed in this paper under real conditions show that our model is reliable and effective.

2 The New Information Priority Accumulated Grey Model with Simpson

In this section, the definition of the new information priority accumulated generation is first given in the subsection 2.1 and discussed its relationship with one-order accumulated generation in the traditional grey system theory. Then the modelling process of the classic grey model is introduced. Finally, a new information priority accumulated grey model with Simpson (NIP-SGM) was proposed in this paper, the definition and other details of the proposed model is given in the subsection 2.3.

2.1 The new information priority accumulated generating operation

The new information priority principle in the grey system theory holds that the cognitive effect of new information is greater than that of old information. At the same time, mining the weights of new and old information in the model establishment can get more suitable for the development law of such information.

Definition 1: Set the original sequence $R^{(0)}=\left(r^{(0)}(1),r^{(0)}(2),\ldots,r^{(0)}(n)\right)$, and accumulate new information priorities for $R^{(0)}$ to generate $R^{(1)}=\left(r^{(1)}(1),r^{(1)}(2),\ldots,r^{(1)}(n)\right)$, where

$$r^{(1)}(k)=\begin{cases}r^{(0)}(1),k=1\\ \alpha r^{(1)}(k-1)+r^{(0)}(k),k=2,3,\ldots,n,\alpha\in(0,1)\end{cases} \tag{1}$$

It should be noted that, when $\alpha=1$, the new information priority accumulated generating operator (NIP-AGO) degenerates to the one-order accumulated generating operator (1-AGO).

Definition 2: The original non-negative sequence $R^{(0)}$ can also be generated from the sequence $R^{(1)}$ through the new information priority inverse accumulation operation, which is

$$r^{(0)}(k)=\begin{cases}r^{(1)}(1),k=1\\ r^{(1)}(k)-\alpha r^{(1)}(k-1),k=2,3,\ldots,n,\alpha\in(0,1)\end{cases} \tag{2}$$

Similarly, when $\alpha=1$, the new information priority inverse accumulated generating operator (NIP-IAGO) degenerates to the one-order inverse accumulated generating operator (1-IAGO).

2.2 The classic grey GM (1,1) model

The classic grey GM(1,1) model is established as follows:

Assume the sequence $X^{(1)}=\left(x^{(1)}(1),x^{(1)}(2),\ldots,x^{(1)}(n)\right)$ be the accumulated generating operator (1-AGO) of $X^{(0)}=\left(x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\right)$, which $x^{(1)}(k)=\sum_{i=1}^{k}x^{(0)}(i)(k=1,2,\ldots n)$, establish a grey differential equation for it:

$$\frac{dx^{(1)}(t)}{dt}+a_1x^{(1)}(t)=b_1 \tag{3}$$

where a_1 is the development coefficient, b_1 is grey action.The background value sequences for generating $X^{(1)}$ is $Z_1^{(1)} = \left(z_1^{(1)}(2), z_1^{(1)}(3), \ldots, z_1^{(1)}(n)\right)$, where:

$$z_1(k) = 0.5(x^{(1)}(k-1) + x^{(1)}(k)), k = 2,3,\ldots,n \tag{4}$$

Integrating and discretizing Eq.(3) gives:

$$x^{(0)}(k) + a_1 z_1^{(1)}(k) = b_1, k = 2,3,\ldots,n \tag{5}$$

Grey parameter $u_1 = [a_1, b_1]^T$, then the least square estimation parameter sequence of Eq. (5) satisfies:

$$\hat{u}_1 = \left(B_1^T B_1\right)^{-1} B_1^T Y_1 \tag{6}$$

where:

$$B_1 = \begin{pmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{pmatrix}, \quad Y_1 = \begin{pmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{pmatrix} \tag{7}$$

For simplicity of calculation, set

$$Z_1^{(1)} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \frac{1}{2} & 0 & \cdots & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & \cdots & \frac{1}{2} \end{pmatrix} \begin{pmatrix} x^{(1)}(1) \\ x^{(1)}(2) \\ x^{(1)}(3) \\ \vdots \\ x^{(1)}(n) \end{pmatrix} \tag{8}$$

Therefore, the matrix B_1 is represented as $B_1 = \left(-\left(Z_1^{(1)}\right)_{(n-1)\times 1}, e_{(n-1)\times 1}\right)$, where $e_{(n-1)\times 1}$ is the $(n-1)\times 1$ -dimensional identity matrix.

Then the time response sequence of the GM (1,1) model can be written as follows:

$$\hat{x}^{(1)}(k+1) = \left(x^{(0)}(1) - \frac{b_1}{a_1}\right) e^{-a_1 k} + \frac{b_1}{a_1}, k = 1,2,\ldots,n \tag{9}$$

The predicted value $\hat{x}^{(0)}$ after reduction:

$$\hat{x}^{(0)}(k+1)=\hat{x}^{(1)}(k+1)-\hat{x}^{(1)}(k)=\left(1-e^{a_1}\right)\left(\hat{x}^{(0)}(1)-\frac{b_1}{a_1}\right)e^{-a_1 k} \tag{10}$$

2.3 The new information priority accumulated grey NIP-SGM (1,1) model with Simpson

Set the original data sequence $S^{(0)}=\left(s^{(0)}(1),s^{(0)}(2),\ldots,s^{(0)}(n)\right)$, and the new information priority accumulation generation method proposed by subsection 2.1 for $S^{(0)}$ gets $S^{(1)}=\left(s^{(1)}(1),s^{(1)}(2),\ldots,s^{(1)}(n)\right)$, The following studies are based on this.

With the Simpson numerical integration formula, considering the integral of Eq. (3) on $[k-1,k+1]$, we have

$$\int_{k-1}^{k+1}ds^{(1)}(t)+a_2\int_{k-1}^{k+1}s^{(1)}(t)\,dt=b_2\int_{k-1}^{k+1}dt,k=2,3,\ldots,n-1 \tag{11}$$

Eq. (12) can be further expressed as

$$s^{(1)}(k+1)-s^{(1)}(k-1)+a_2\int_{k-1}^{k+1}s^{(1)}(t)\,dt=2b_2,k=2,3,\ldots,n-1 \tag{12}$$

Using the Simpson integral formula, we have

$$\int_{k-1}^{k+1}s^{(1)}(t)\,dt=\frac{1}{3}\left[s^{(1)}(k-1)+4s^{(1)}(k)+s^{(1)}(k+1)\right] \tag{13}$$

Eq. (14) can be converted into

$$\begin{aligned}&s^{(1)}(k+1)-s^{(1)}(k-1)+\frac{a_2}{3}\left(s^{(1)}(k-1)+4s^{(1)}(k)+s^{(1)}(k+1)\right)\\&=2b_2,k=2,3,\ldots,n-1\end{aligned} \tag{14}$$

The background value sequence $z_2^{(1)}(k)$ can be expressed as:

$$z_2^{(1)}(k)=\frac{1}{6}\left(s^{(1)}(k-1)+4s^{(1)}(k)+s^{(1)}(k+1)\right) \tag{15}$$

Definition 3: Set the raw data sequence $S^{(0)}=\left(s^{(0)}(1),s^{(0)}(2),\ldots,s^{(0)}(n)\right)$, and the new information priority accumulated generating sequence $S^{(1)}=\left(s^{(1)}(1),s^{(1)}(2),\ldots,s^{(1)}(n)\right)$ have the same definition as those in Definition 1 and 2 and the parameters a_2,b_2 and the improved background value sequence $Z_2^{(1)}$ are described as above. The whitening differential equation

$$\frac{ds^{(1)}(t)}{dt}+a_2 s^{(1)}(t)=b_2 \tag{16}$$

Is named as the new information accumulated grey model with Simpson (abbreviated as NIP-SGM), the discrete form of the proposed model can be expressed as

$$s^{(0)}(k)+a_2 z_2^{(1)}(k)=b_2, k=2,3,\ldots,n \tag{17}$$

Set $u_2=[a_2,b_2]^T$ as the parameter column, and apply the principle of the least square method to meet the following requirements:

$$\hat{u}_2=\left(B_2^T B_2\right)^{-1} B_2^T Y_2 \tag{18}$$

In which:

$$B_2=\begin{pmatrix} -\frac{s^{(1)}(1)+4s^{(1)}(2)+s^{(1)}(3)}{6} & 1 \\ -\frac{s^{(1)}(2)+4s^{(1)}(3)+s^{(1)}(4)}{6} & 1 \\ \vdots & 1 \\ -\frac{s^{(1)}(n-2)+4s^{(1)}(n-1)+s^{(1)}(n)}{6} & 1 \end{pmatrix}, \quad Y_2=\begin{pmatrix} \frac{s^{(1)}(3)-s^{(1)}(1)}{2} \\ \frac{s^{(1)}(4)-s^{(1)}(2)}{2} \\ \vdots \\ \frac{s^{(1)}(n)-s^{(1)}(n-2)}{2} \end{pmatrix} \tag{19}$$

The matrix B_2 is expressed as $B_2=\left(-\left(Z_2^{(1)}\right)_{(n-2)\times 1}, e_{(n-2)\times 1}\right)$, where $e_{(n-2)\times 1}$ is the unit matrix of $(n-2)\times 1$ dimension, $Z_2^{(1)}$ is

$$Z_2^{(1)}=\begin{pmatrix} \frac{1}{6} & \frac{2}{3} & \frac{1}{6} & 0 & 0 & \cdots & 0 & 0 \\ 0 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} & 0 & \cdots & 0 & 0 \\ 0 & 0 & \frac{1}{6} & \frac{2}{3} & \frac{1}{6} & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & 0 & \cdots & \frac{2}{3} & \frac{1}{6} \end{pmatrix} \begin{pmatrix} s^{(1)}(1) \\ s^{(1)}(2) \\ s^{(1)}(3) \\ \vdots \\ s^{(1)}(n) \end{pmatrix} \tag{20}$$

Then the time response sequence of the NIP-SGM (1,1) model can be written as follows:

$$\hat{s}^{(1)}\left(k+1\right)=\left(s^{(0)}\left(1\right)-\frac{b_2}{a_2}\right)e^{-a_1 k}+\frac{b_2}{a_2}, k=1,2,\ldots,n \tag{21}$$

Finally, according to the Eq.(2) of this paper, the predicted value $\hat{s}^{(0)}$, which is restored by the new information priority inverse accumulation operation, is calculated.

3 Application

In this section, we set the classic grey GM (1,1) model is described in subsection 2.2 as the benchmark model, and the proposed model and the benchmark model are both utilized to forecast the carbon dioxide emissions in India and Bangladesh. Furthermore, four existing improved grey model also are employed to verify the reliability of the model comprehensively.

3.1 Metrics for evaluating model performance

In order to accurately evaluate the performance of the model, a unified metric needs to be established. In this paper, we use the mean absolute error (MAE), root mean square error ($RMSE$), root mean square percentage error ($RMSPE$), mean absolute percentage error ($MAPE$) and regression coefficient (R) the total of five model evaluation indicators to evaluate the model.

The mean absolute error (MAE) is calculated as follows:

$$MAE=\frac{1}{n}\sum_{k=1}^{n}\left|\hat{x}^{(0)}\left(k\right)-x^{(0)}\left(k\right)\right| \tag{22}$$

The root mean square error ($RMSE$) is calculated as follows:

$$RMSE=\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left(\hat{x}^{(0)}\left(k\right)-x^{(0)}\left(k\right)\right)^2} \tag{23}$$

The root mean square percentage error ($RMSPE$) is calculated as follows:

$$RMSPE=\sqrt{\frac{1}{n}\sum_{k=1}^{n}\left|\frac{\hat{x}^{(0)}\left(k\right)-x^{(0)}\left(k\right)}{x^{(0)}\left(k\right)}\right|^2} \tag{24}$$

The mean absolute percentage error ($MAPE$) is calculated as follows:

$$MAPE=\frac{1}{n}\sum_{k=1}^{n}\frac{\left|\hat{x}^{(0)}\left(k\right)-x^{(0)}\left(k\right)\right|}{x^{(0)}\left(k\right)}\times 100\% \tag{25}$$

The regression coefficient (R) is calculated as follows:

$$R=\frac{\sum_{k=1}^{n}\left(\hat{x}^{(0)}(k)-\bar{\hat{x}}^{(0)}(k)\right)\left(x^{(0)}(k)-\bar{x}^{(0)}(k)\right)}{\sqrt{\sum_{k=1}^{n}\left(\hat{x}^{(0)}(k)-\bar{\hat{x}}^{(0)}(k)\right)^{2}\left(x^{(0)}(k)-\bar{x}^{(0)}(k)\right)^{2}}} \tag{26}$$

where $\hat{x}^{(0)}(k)$ represents the predicted value, $x^{(0)}(k)$ represents the original value, $\bar{\hat{x}}^{(0)}(k)$ represents the average of $\hat{x}^{(0)}(k)$, $\bar{x}^{(0)}(k)$ represents the average of $x^{(0)}(k)$ and n represents the size of the data set to be tested.

3.2 Collection and processing of carbon dioxide emission data

In this paper, we use MATLAB software to program, and use the historical data of India and Bangladesh in 1997-2012 for 16 years to predict the carbon dioxide emissions in 2013-2015 for three years, change the size of α in the new information priority accumulation generation method: from 0.01 to 0.99 in steps of 0.01. Compare the value of $MAPE$ in 2013-2015 under each α value, select the value of α with the lowest $MAPE$ value, which is the most suitable for this group of data, and then predict the carbon dioxide emissions in 2016-2025 for a total of 7 years, and calculate the value of MAE, $RMSE$, $RMSPE$ and $MAPE$ in 2016-2018.

The rest of the comparative models use the historical data of 16 years from 1997 to 2012 to directly predict the carbon dioxide emissions of 3 years from 2016 to 2018, and use MATLAB software to get the regression chart under each function prediction value, and compare the regression coefficient to achieve the model prediction accuracy comparison. Then calculate the values of MAE, $RMSE$, $RMSPE$ and $MAPE$ in each model from 2016 to 2018 and compare them with the improved model.

3.3 Establishment of grey prediction models

In this paper, the carbon dioxide emission data in India and Bangladesh are used as the raw data sequence. Firstly, according to the Eq. (6) in section 1.2, the development coefficient and the grey action of the classic grey GM (1,1) model for India are -0.0570 and 753.9804, respectively. And the development coefficient and the grey action of the classic grey GM (1,1) model for Bangladesh are -0.0684 and 18.5709, respectively.

Table 1. The predictive value of CO_2 emissions in the two countries from 2016 to 2025

Years	CO_2 emissions in India / million tonnes		CO_2 emissions in Bangladesh / million tonnes	
	GM(1,1)	NIP-SGM(1,1)	GM(1,1)	NIP-SGM(1,1)
2016	2304.5779	2279.5029	79.5915	78.1352
2017	2439.7546	2408.1459	85.6974	83.8561
2018	2582.8602	2543.6290	92.2718	89.9818
2019	2734.3597	2686.3041	99.3505	96.5410
2020	2894.7455	2836.5571	106.9722	103.5642
2021	3064.5389	2994.7904	115.1787	111.0845
2022	3244.2916	3161.4280	124.0148	119.1368
2023	3434.5879	3336.9161	133.5287	127.7589
2024	3636.0461	3521.7248	143.7725	136.9911
2025	3849.3210	3716.3493	154.8021	146.8766

Moreover, according to the modelling process of the new information priority accumulated grey NIP-SGM model with Simpson. The development coefficient and the grey action of the NIP-SGM (1,1) model for India are -0.0570 and 753.9804 respectively, the new information priority accumulated generating parameter α is 0.99. And the development coefficient and the grey action of the NIP-SGM (1,1) model for Bangladesh are -0.0684 and 18.5709 respectively, the new information priority accumulated generating parameter α is 0.99. The predicted values of classic grey GM (1,1) model and NIP-SGM (1,1) can be further calculated respectively according to Eq. (10) and Eq. (21), which are tabulated in Table 1.

In this paper, a regression model is established to compare the prediction effect of the model. Four existing improved grey models were compared with the benchmark model and the proposed model, which including the NGM (1,1) prediction model 0, the DGM (1,1) prediction model 0, the SAIGM(1,1) prediction model 0and the SGM(1,1) prediction model 0. The prediction results of different grey models for the carbon dioxide emissions in India and Bangladesh are drawn in Figs. 1 and 2.

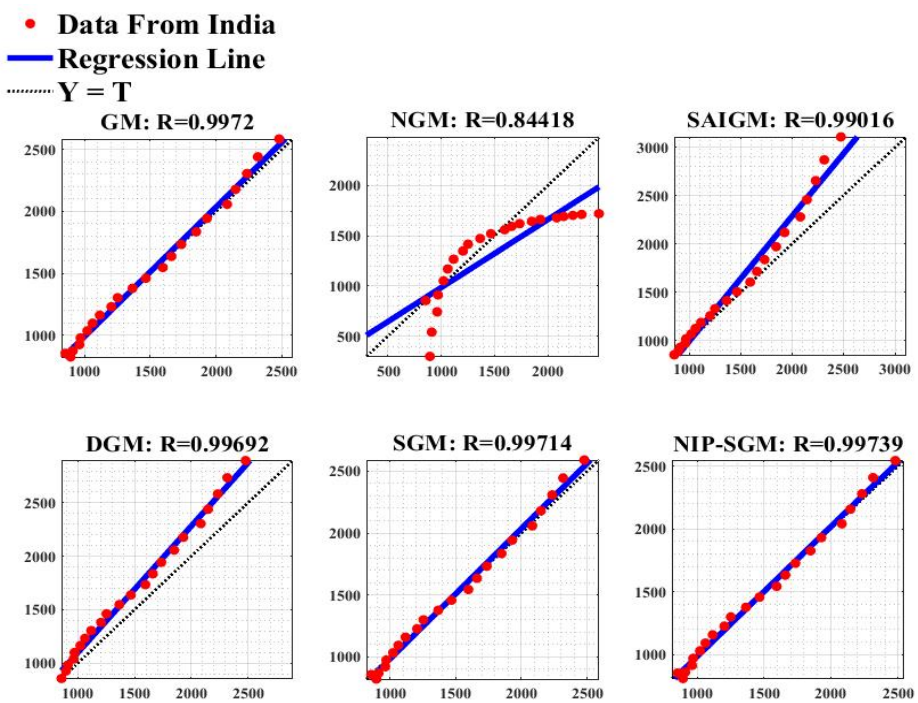

Fig. 1. Regression plots of each model in Indian data

It can be seen from Fig. 1 that the carbon dioxide emission data from India are employed to construct grey prediction models, the largest regression coefficient is 0.99739, which belongs to the NIP-SGM (1,1) model, indicating that the regression effect is the best and the prediction effect is the best, followed by the GM(1,1) model, the SGM(1,1) model, the DGM(1,1) model, the SAIGM(1,1) model and the NGM(1,1) model respectively.

According to Fig. 2, the carbon dioxide emission data from Bangladesh are employed to construct grey prediction models, the largest regression coefficient value is 0.99775, which also belongs to the NIP-SGM (1,1) model, indicating that the regression effect is the best and the prediction effect is the best, followed by the SGM (1,1) model, the GM (1,1) model, the SAIGM (1,1) model, the DGM (1,1) model and the NGM (1,1) model respectively.

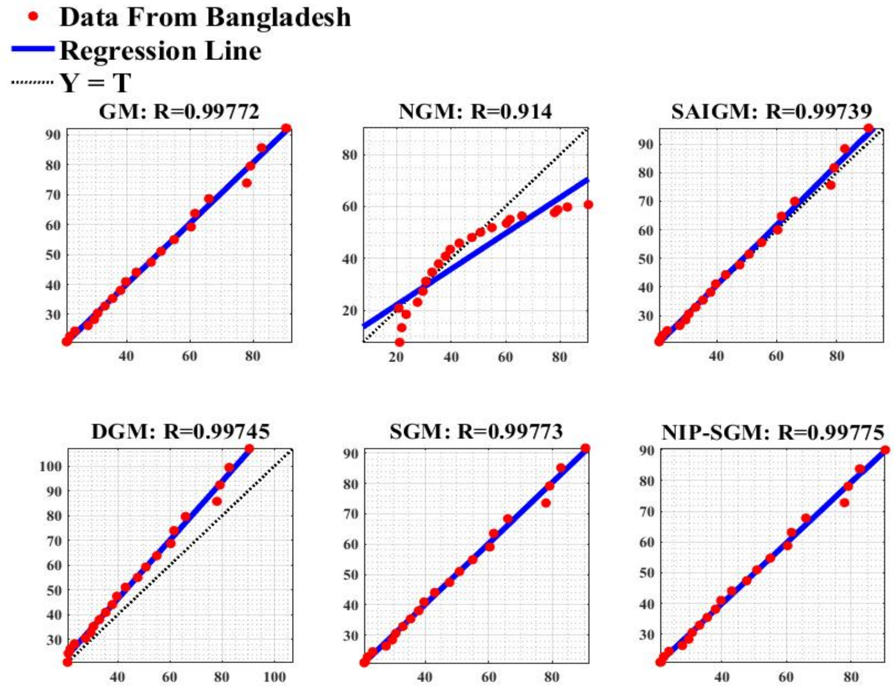

Fig. 2. Regression plots of each model in Bangladesh data

3.4 Accuracy comparison of grey prediction model

This paper not only compares the accuracy of the classic GM (1,1) prediction model with the improved model, but also compares the NGM (1,1) prediction model, the DGM (1,1) prediction model, the SAIGM (1,1) prediction model and the SGM (1,1) prediction model. Then the metrics for evaluating models are applied to analyze the prediction effect of the modes, and the calculated mean absolute error (MAE), root mean square error ($RMSE$), root mean square percentage error ($RMSPE$) and mean absolute percentage error ($MAPE$) of each model are listed in Table 2 for details.

Table 2. Evaluation metrics value of each grey model

			Data form India			
	GM	**SGM**	**NGM**	**SAIGM**	**DGM**	**NIP-SGM**
MAE	74.2569	78.8536	473.2476	401.9888	296.1945	**50.2791**
MAPE/%	4.2131	4.4725	26.8033	22.7651	16.8395	**2.8568**
RMSE	101.3611	107.5476	638.1003	542.8703	396.2255	**69.6411**
RMSPE/%	4.3040	4.5636	26.9536	22.9370	16.8683	**2.9670**
			Data form Bangladesh			
	GM	**SGM**	**NGM**	**SAIGM**	**DGM**	**NIP-SGM**
MAE	1.3135	0.9513	18.2495	3.3282	11.6501	**0.6532**
MAPE/%	2.0615	1.4897	28.7657	5.2335	18.4454	**1.0562**
RMSE	2.0394	1.6227	24.6472	4.6384	15.6208	**0.9230**
RMSPE/%	2.4116	1.9282	28.9200	5.4449	18.5026	**1.1300**

As can be observed from Table 2, the four error indices of the NIP-SGM model were significantly lower than those of the other five models in forecasting the carbon dioxide emissions in India and Bangladesh.

This also indicates that NIP-SGM has better prediction performance than other models. In order to more intuitively observe the prediction accuracy of each model, this paper draws a radar chart of the mean absolute percentage error ($MAPE$) of each model, as shown in Fig. 3. A histogram is drawn to compare the root mean square percentage error ($RMSPE$) of each model, as shown in Fig. 4.

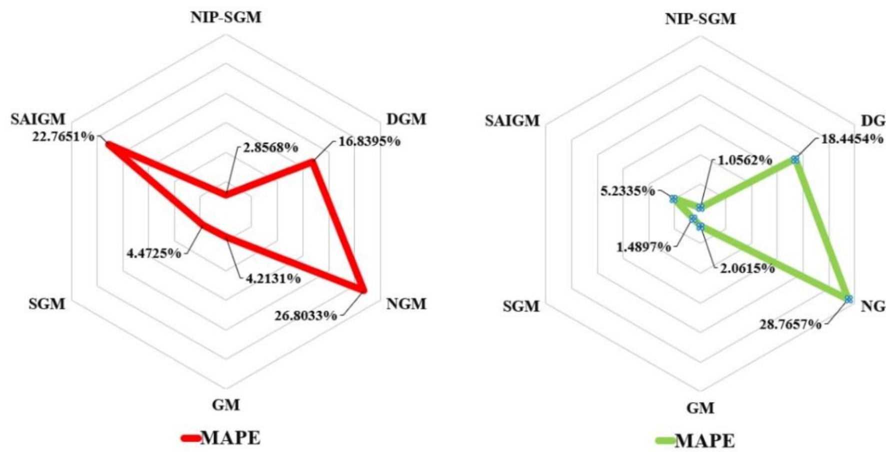

Fig. 3. MAPE comparison of each model

According to Figs. 3 and 4, the prediction accuracy of the NGM (1,1) model and the DGM (1,1) model is similar, but neither can forecast the carbon dioxide emissions well, The prediction effect of SAIGM is not satisfactory, and the error results show that the prediction results for different countries vary greatly. Although both the classic grey GM (1,1) model and the SGM (1,1) showed high prediction accuracy in the prediction of the two countries, NIP-SGM was still superior to these models. This results further confirmed that the NIP-SGM (1,1) model proposed in this paper improves the prediction accuracy of the model.

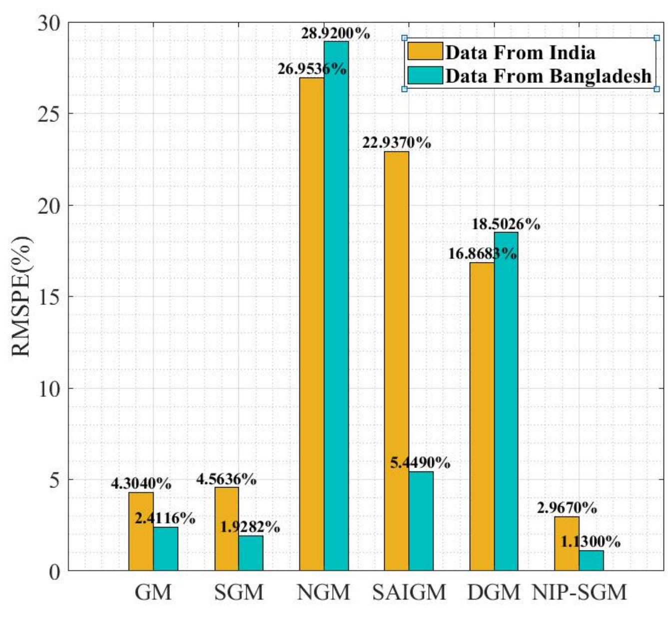

Fig. 4. RMSPE comparison of each model

4 Conclusion

In our research work, a novel grey model called the NIP-SGM(1,1) is creatively proposed based on the principle of the new information priority and Simpson numerical integral formula is employed to boost the prediction accuracy of the proposed model. In the application part, the carbon dioxide emissions of India and Bangladesh are applied to construct the grey prediction models, which play a significant role in greenhouse gas emissions in the Asia-pacific region. The results show that the root mean square percentage error ($RMSPE$) of the proposed model between the predicted value and the actual value is within 3%, the mean absolute percentage error ($MAPE$) is also less than 3%, and the regression coefficient (R) is greater than 0.997, which reveals that the model is feasible. The prediction model established in this paper, whose evaluation metrics are less than the other five existing models, shows that the prediction of the NIP-SGM (1,1) model is more accurate and applicable to the prediction of carbon dioxide emissions.

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Competing Interests

Authors have declared that no competing interests exist.

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