



# Forecasting China's CO<sub>2</sub> emissions by considering interaction of bilateral FDI using the improved grey multivariable Verhulst model

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## Abstract

Because of the harmful influence of CO<sub>2</sub> emissions on the environment and humans, issues related to CO<sub>2</sub> emissions have received considerable attention in recent years. Based on the pollution haven hypothesis and pollution halo effect, the uncertain effect of bilateral foreign direct investment (FDI) on CO<sub>2</sub> emissions has recently been in focus. Moreover, because of the opposing capital flow of bilateral FDI, the interaction between inward FDI (IFDI) and outward FDI (OFDI) might have a trade-off effect on CO<sub>2</sub> emissions. The accurate forecasting of CO<sub>2</sub> emissions in China in light of effect of the bilateral FDI is important since the government can use it to regulate emissions' reduction. The grey multivariable Verhulst model (GMVM) was formulated in this paper with the goal of forecasting CO<sub>2</sub> emissions in China by considering the nonlinear, independent, and interaction-related effects of bilateral FDI on them. To enhance the accuracy of prediction, this paper used the Fourier series and the grey prediction model for residual modifications. The empirical results showed that the IFDI and the item of the interaction of bilateral FDI promoted CO<sub>2</sub> emissions, whereas OFDI reduced them in China. These results also verified the higher precision of the improved GMVM relative to other models. This paper also used improved GMVM to further forecast CO<sub>2</sub> emissions and provided suggestions for the Chinese government to plan for foreign investment, including selectively implementing bilateral FDI, and focusing on the trade-off in its interaction-related effects.

**Keywords** CO<sub>2</sub> emissions · Bilateral FDI · Grey multivariable Verhulst model · Interaction effect · Residual modification model

## 1 Introduction

With the implementation of the “Reform and Opening Up” policy, the Chinese government has accomplished certain goals of the “bring in and go out” strategy (Zheng and Sheng 2017). The total inward foreign direct investment (IFDI) has since increased remarkably such that China ranks second among the recipients of foreign direct investment (FDI)

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worldwide (Jiang and Fu 2014). With rapid economic development, China is generally transitioning from being an FDI receiving country to becoming an FDI investor, per Dunning's theory of investment development path (Dunning 1981). China's total outward foreign direct investment (OFDI) has been continually growing since the Belt and Road Initiative proposal in 2013. Because bilateral FDI has a spillover effect on economic development through technological improvement, the utilization of foreign capital, and advanced management experience (Ben Hassine et al. 2017; Li and Shao 2016), bilateral FDI is undoubtedly a catalyzer for China's economic development (Leng and Du 2017).

Low standards of environmental regulations, as well as inexpensive energy and labor provided by countries with emerging economies like China's, are attractive for IFDI. However, an increase in IFDI is usually accompanied by several environmental problems, for example the CO<sub>2</sub> emissions. Excessive CO<sub>2</sub> emissions have contributed to greenhouse gas emissions, global warming, and extreme weather patterns that severely damage the environment and harm human health. To deal with this problem, at the UN Climate Change Summit in 2009, China solemnly promised to take measures for CO<sub>2</sub> emissions reduction per unit GDP by 40–45% by the end of 2020 in comparison with emissions in 2005 (Wang and Ye 2017). Therefore, accurately forecasting China's CO<sub>2</sub> emissions can provide a basis for implementing emissions reduction.

Some scholars have discussed the relationship between bilateral FDI and CO<sub>2</sub> emissions. Walter and Ugelow (1979) proposed the pollution haven hypothesis (PHH), which states that developed economies often transfer polluting industries or commodities into developing ones, with comparatively laxer or even scarce environmental regulations, by investing abroad (Antweiler et al. 2001; Copeland and Taylor 1994). Contrary to the PHH, the pollution halo effect (PHE) states that foreign companies with advanced managerial skills and manufacturing technologies are contributed to reducing CO<sub>2</sub> emissions in host countries (Zarsky 1999). Unlike the uncertain effect of IFDI on CO<sub>2</sub> emissions, previous studies have claimed that OFDI positively affects CO<sub>2</sub> emission reduction in home countries through the transfer of highly polluting industries as well as enhancements in environmental protection technologies (Luo and Cheng 2013). Moreover, owing to the different effects of bilateral FDI on CO<sub>2</sub> emissions, its interactions should also be considered an important factor affecting carbon dioxide emissions. Furthermore, in the context of the undefined effects, there is a nonlinear relationship between IFDI and CO<sub>2</sub> emissions. Therefore, excluding the separate effects of bilateral FDI on CO<sub>2</sub> emissions, its interactional effect and nonlinear relationship with carbon dioxide emissions are discussed in this paper.

Because forecasting CO<sub>2</sub> emissions by considering the effects of bilateral FDI is a typical multivariable system problem, the grey multivariable GM(1,N) model, which works well with a small sample and poor information, and does not make any statistical assumption, has drawn considerable research interest. The GM(1,N) model is a grey prediction model with distinctive  $N-1$  related variables. Unlike the grey univariable GM(1,1) model, the GM(1,N) model takes into consideration the relationship of the variables describing system behavior with other relevant ones. Thus, it is better suited for modeling and forecasting in multivariable systems. However, Wang and Ye (2017) claimed that GM(1,N) models, with linear features related to the structure, do not properly reflect the nonlinear relationship between system behavior and other relevant variables, and thus is not appropriate to describe a nonlinear system with a linear model, which can cause great errors. Owing to the nonlinear relationship between bilateral FDI and CO<sub>2</sub> emissions, this paper established a grey multivariable Verhulst GMVM(1,N) model by combining the GM(1,N) model and the Verhulst model to better reflect this nonlinear relationship. The Verhulst model describes processes with saturation and is often implemented to demonstrate

S-shaped data types (Liu and Lin 2010). Because the sequences of the collected data exhibit saturation-related tendencies, the Verhulst prediction model is well suited to them. Furthermore, to improve prediction accuracy, the Fourier series and the residual modification model obtained with the help of GM(1,1) were applied to alter the residual obtained from the proposed GMVM(1,N) model. Finally, the prediction performance of the improved GMVM(1,N) model was verified using the original GM(1,N) and GMVM(1,N) models by applying the mean absolute percentage error (MAPE).

The technical part of the paper is arranged into the following sections. Section 2 reviews literature data relevant to the topics of this paper. Section 3 familiarizes the readers with the GMVM(1,N) model, and as well as the improved GMVM(1,N) model (by implementing an error correction model). Section 4 analyzes CO<sub>2</sub> emissions in China by considering bilateral FDI. Finally, Sect. 5 lists conclusions and suggestions for further work in the research area.

## 2 Literature overview

### 2.1 Effects of bilateral FDI on CO<sub>2</sub> emissions

Because the directions of the capital flows of IFDI and OFDI are opposite, the impacts of CO<sub>2</sub> emissions on the host (home) countries as a consequence of such investments differ. Literature reports that discuss how IFDI affects CO<sub>2</sub> emissions can be divided into three categories. Some scholars have found that IFDI has a direct impact on increasing CO<sub>2</sub> emissions (Zheng and Sheng 2017). Developing countries usually boost economic development by attracting foreign investment. However, as the PHH claims, owing to poor environmental regulations, developed economies often shift highly polluting industries to developing economies, directly resulting in an increase in CO<sub>2</sub> emissions in the latter (Gökmenoğlu and Taspınar 2015; Luo and Li 2012; Walter and Ugelow 1979). On the contrary, some scholars claim that IFDI has a negative effect on CO<sub>2</sub> emissions (Zhu et al. 2016). Increasing IFDI has a spillover effect on leads to an improvement in management experience and technology, especially the upgrading of energy-related technologies, which will help the host country reduce CO<sub>2</sub> (Hao and Liu 2015; Xu and Liu 2016; Zhu et al. 2016). Other researchers have claimed that the relationship between IFDI and CO<sub>2</sub> emissions is unclear because of regional differences, different sources of investment, and the threshold effect (Wang and Pei 2014; Wang and Ye 2017).

That OFDI indirectly affects CO<sub>2</sub> emissions in the home country through industrial structuring, and reverse spillover effect on technology is accepted in the literature (Fei 2014). On the one hand, according to Kojima's theory of marginal industry expansion, a country first transfers its disadvantaged industries, especially industries with high energy consumption and carbon dioxide emissions, to countries or regions with comparative advantages (Kojima 1978). On the other hand, with an increase in OFDI, the home country undergoes a technological upgrade and the optimization of its industrial structure through the reverse spillover effect, thereby reducing CO<sub>2</sub> emissions (Fei 2014; Luo and Cheng 2013).

Although some previous reports have been dedicated to an assessment of how bilateral FDI affects CO<sub>2</sub> emissions independently, little research has focused on the interaction effects of IFDI and OFDI on CO<sub>2</sub> emissions. Wang and Hu (2013) and Wang and Wang (2017) analyzed the effects of the productivity of bilateral FDI in the service and

manufacturing industries, respectively. Their results suggest that the interaction effect of bilateral FDI promotes productivity in these two industries. Zhang (2017) discussed the impact of bilateral FDI and financial development on the optimization of industrial structure, and the results revealed that the interaction of bilateral FDI hinders the optimization of industrial structure because it is uncoordinated.

Based on the above literature review, the general conclusion is that there is a close relationship between bilateral FDI and CO<sub>2</sub> emissions, but there is no consensus on the impact of the former on the latter. Moreover, because of the differing impact of bilateral FDI on CO<sub>2</sub> emissions, the latter serve as a trade-off between the influence of IFDI and that of OFDI.

## 2.2 Nonlinear relationship between bilateral FDI and CO<sub>2</sub> emissions

With increasing global investment and an emphasis on environmental preservation, many researchers have analyzed the linear relationship between bilateral FDI and CO<sub>2</sub> emissions, and a few have also examined the nonlinear relationship between them (Park et al. 2015; Zhu et al. 2016). Huang (2017) claimed that IFDI has a significant nonlinear threshold effect on the intensity of CO<sub>2</sub> emissions in China, whereas this effect is varied in different regions of the country. Zhou et al. (2015) claimed a nonlinear relationship between FDI and the environment of the host country by using the correlation between economic growth and CO<sub>2</sub> emissions according to the environmental Kuznets curve (EKC) hypothesis. In addition, Sulkowski and White (2015) expanded the application of the Kuznets curve and found that it can be used to relate happiness with the economic development of different countries.

A review of the literature shows a nonlinear relationship between bilateral FDI and CO<sub>2</sub> emissions. Therefore, it is important to consider the nonlinear effect of bilateral FDI on CO<sub>2</sub> emissions forecasting.

## 2.3 Forecasting China's CO<sub>2</sub> emissions

As it is an emerging economy, energy consumption in China is constantly growing with accelerating economic development. Thus, the trend of CO<sub>2</sub> emissions is a concern. Various methods have been applied to forecast CO<sub>2</sub> emissions including spatial econometrics, series analysis, and Artificial Intelligence, and all have delivered a good performance. (Chen 2015; Garcia-Martos et al. 2013; Sun et al. 2017; Xu et al. 2017). Usually, these methods require a large number of samples and the data need to conform to statistical assumptions to reduce the random disturbance caused by uncertainty (Feng et al. 2012). Thus, some scholars have applied both GM(1,1) as well as GM(1,N) models to estimate CO<sub>2</sub> emissions due to the characteristics of the grey model. Pao et al. (2012) applied the nonlinear grey Bernoulli NGBM(1,1) model to forecast China's CO<sub>2</sub> emissions and proposed an iterative numerical method to optimize the parameters. Wu et al. (2015) forecasted emissions of CO<sub>2</sub> in BRICS countries using a rolling multivariable grey forecasting model by considering GDP growth and energy consumption as related influential factors. Ding et al. (2017) applied the grey model integrated with an optimization algorithm to predict CO<sub>2</sub> emissions in China using fuel combustion data and considered the GDP, urban population, and energy use as relevant factors. Wang and Ye (2017) established a nonlinear

grey multivariable model for CO<sub>2</sub> emission predictions in China using fossil fuel-based energy consumption data and considering the effects of the GDP.

In the above studies, the background optimization approach has been widely utilized to enhance the accuracy of the grey prediction model. However, the original system behavior variable and other relevant variables are sacrificed for the sake of accuracy of the prediction. Therefore, using the residual modification model to improve prediction accuracy without changing the original parameters is the main goal of this paper. With regard to selecting the relevant factors, previous studies chose economic development according to the EKC hypothesis and energy consumption as relevant factors. This paper predicts CO<sub>2</sub> emissions based on the relationship between CO<sub>2</sub> emissions and bilateral FDI. This not only has theoretical support, but can also yield useful policy suggestions for the government on foreign investment and emissions reduction.

### 3 Methodologies

In 1982, Professor Deng introduced grey system theory to the whole world, which was suitable for the partial unknown, small samples, and poor information system modeling (Ye et al. 2018). The grey prediction model is a significant component of grey system theory that applies to various fields, such as tourism (Hu 2017), energy (Wang and Ye 2017), and the economy (Jiang et al. 2019). Of grey prediction models, the GM(1,N) model is widely used. It is a typical causal forecasting model with fully considering the impact of relative variables on the dependent variable (Zeng et al. 2016). The literature review has shown a relationship between CO<sub>2</sub> emissions and bilateral FDI, the specific form of which is unknown. The system constructed by considering CO<sub>2</sub> emissions and bilateral FDI has the characteristics of a grey system: namely that the information is partially known. Therefore, it is appropriate to adopt the GM(1,N) model to analyze and predict the relationship between CO<sub>2</sub> emissions and bilateral FDI. Furthermore, for better prediction accuracy and to overcome the drawbacks of models mentioned in Sect. 2.3, this subsection describes an improved grey multivariable Verhulst model (GMVM). Firstly, our proposed GMVM(1,N) model was combined with the Verhulst model (containing the traditional GM(1,N) model) to obtain an adequate capacity to analyze the data with nonlinear characteristics. Secondly, the prediction accuracy of the proposed model was improved by combining it with the residual modification model without damaging the original parameters. The specific modeling procedure was provided as below.

#### 3.1 Grey multivariable Verhulst model

The grey multivariable GM(1,N) model has been widely applied to predict system behavior variable considering the effect of the relevant variables. However, by reviewing the literatures, the traditional GM(1,N) models have linear features with regard to structure, namely the traditional GM(1,N) model cannot reflect the nonlinear relationship between FDI and CO<sub>2</sub> emissions. Therefore, a GMVM(1,N) model was constructed by combining the GM(1,N) and the Verhulst models. Moreover, to improve the prediction accuracy of the GMVM(1,N) model, the grey control parameter of GM(1,1) was introduced to it using GMC(1,N)-based modeling (Tien 2012).

We assumed that  $X_1^{(0)} = (x_1^{(0)}(1), x_1^{(0)}(2), \dots, x_1^{(0)}(n))$  is an original dataset for the characteristic sequence of a system (or a dependent variable), and that

$X_i^{(0)} = (x_i^{(0)}(1), x_i^{(0)}(2), \dots, x_i^{(0)}(n))$ , where  $i = 2, 3, \dots, N$  are the corresponding (or independent) variable sequences possessing certain relationship with the  $X_1^{(0)}$  sequence.

Thus, the new sequence  $X_i^{(1)} = (x_i^{(1)}(1), x_i^{(1)}(2), \dots, x_i^{(1)}(n))$  can be obtained from  $X_i^{(0)}$  by the first-order accumulated generating operation (1-AGO) as follows:

$$x_i^{(1)}(k) = \sum_{j=1}^k x_i^{(0)}(j), \quad k = 1, 2, \dots, n. \tag{1}$$

We assume that the background value  $z_1^{(1)}(k)$  is the adjoining mean generated sequence of  $X_1^{(1)}$ .

$$z_1^{(1)}(k) = 0.5 \times (x_1^{(1)}(k) + x_1^{(1)}(k - 1)). \tag{2}$$

A grey control parameter term  $u$  similar to a parameter in the GM(1,1) model is added to the prediction model. Then,

$$x_1^{(0)}(k) + az_1^{(1)}(k) = \sum_{i=2}^n b_i (x_i^{(1)}(k))^2 + u \tag{3}$$

is called a grey multivariable Verhulst GMVM(1,N) model.

Then,

$$\frac{dx_1^{(1)}}{dt} + ax_1^{(1)} = \sum_{i=2}^n b_i (x_i^{(1)}(k))^2 + u \tag{4}$$

is a whitenization equation of the GMVM(1,N) model, where  $a$  is a development coefficient,  $b_i (x_i^{(1)}(k))^2$  and  $b_i$  are the driving term and a driving coefficient, respectively;  $u$  is the grey control parameter.

$a$ ,  $b_i$ , and  $u$  can be calculated by the original least squares (OLS) method:

$$[a, b_i, u]^T = (B^T B)^{-1} B^T y \tag{5}$$

$$B = \begin{bmatrix} -z_1^{(1)}(2) & (x_2^{(1)}(2))^2 & \dots & (x_N^{(1)}(2))^2 & 1 \\ -z_1^{(1)}(3) & (x_2^{(1)}(3))^2 & \dots & (x_N^{(1)}(3))^2 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -z_1^{(1)}(n) & (x_2^{(1)}(n))^2 & \dots & (x_N^{(1)}(n))^2 & 1 \end{bmatrix} \tag{6}$$

and

$$y = [x_1^{(0)}(2), x_1^{(0)}(3), \dots, x_1^{(0)}(n)]^T. \tag{7}$$

The approximate time response sequence of the GMVM(1,N) model can be represented as:

$$\hat{x}_1^{(1)}(k) = \left[ x_1^{(0)}(1) - \frac{1}{a} \sum_{i=2}^n b_i \left( x_i^{(1)}(k) \right)^2 + \frac{u}{a} \right] e^{-a(k-1)} + \left[ \frac{1}{a} \sum_{i=2}^n b_i \left( x_i^{(1)}(k) \right)^2 + \frac{u}{a} \right]. \tag{8}$$

Finally, by implementing the inverse accumulated generating operation (IAGO), the predicted value  $x_k^{(0)}$  can be expressed as follows:

$$\hat{x}_1^{(0)}(k) = \hat{x}_1^{(1)}(k) - \hat{x}_1^{(1)}(k - 1), \quad k = 2, 3, \dots, n \tag{9}$$

where  $\hat{x}_1^{(1)}(1) = x_1^{(0)}(1)$ .

### 3.2 Improved grey multivariable Verhulst model

The accuracy of prediction was improved by using the Fourier series and the GM(1,1) model to modify the residuals produced by the proposed GMVM(1,N) model, shortened and called as RGMVM(1,N) and FGMVM(1,N), respectively. The resulting improved grey prediction model obtained by combining GMVM(1,N) with the residual modification models is given by following:

*Step 1* Following the above procedure, the predicted GMVM(1,N) value,  $\hat{x}_i^{(0)}$ , can be generated.

*Step 2* Generate the sequence of residual values  $\epsilon_k^{(0)} = (\epsilon_2^{(0)}, \epsilon_3^{(0)}, \dots, \epsilon_n^{(0)})$  based on the following equation:

$$\epsilon_k^{(0)} = x_1^{(0)}(k) - \hat{x}_1^{(0)}(k), \quad k = 2, 3, \dots, n \tag{10}$$

*Step 3* Use the Fourier series and the GM(1,1) model to generate the predicted residual  $\hat{\epsilon}_k^{(0)}$  values. For details, refer to ‘‘Appendices 1 and 2.’’

*Step 4* To predict RGMVM(1,N), FGMVM(1,N), and  $x_1^{r(0)}(k)$  values, the following equation can be used:

$$x_1^{r(0)}(k) = \hat{x}_1^{(0)} + \hat{\epsilon}_k^{(0)}, \quad k = 2, 3, \dots, n. \tag{11}$$

### 3.3 Evaluating prediction accuracy

We applied the mean absolute percentage error (MAPE) to assess prediction performance and to compare the predicted values obtained using different methods. MAPE with respect to  $x_k^{(0)}$  is

$$\text{MAPE} = \frac{1}{n} \sum_{k=1}^n \frac{|x_1^{(0)}(k) - x_1^{r(0)}(k)|}{x_1^{(0)}(k)}. \tag{12}$$

Lewis (1982) proposed the MAPE criterion to examine models.  $\text{MAPE} \leq 10\%$  corresponds to a high-quality forecast; MAPE values in the 10–20% range demonstrate good accuracy, and those in the 20–50% range and above 50% indicate models with reasonable and weak forecasts, respectively.

### 3.4 Validation of the improved grey prediction model

Validity verification of the improved grey prediction models was performed using numerical case proposed by Liu and Lin to examine prediction accuracy of the GM(1,N), GMVM(1,N), RGMVM(1,N), and FGMVM(1,N) models. The data sequence of the system’s characteristics is  $X_1^{(0)} = (2.874, 3.278, 3.307, 3.39, 3.679)$ , and the data sequence of relevant factor is  $X_2^{(0)} = (7.04, 7.645, 8.075, 8.53, 8, 774)$ .

The prediction results of the GM(1,N), GMVM(1,N), RGMVM(1,N), and FGMVM(1,N) models are summarized in Table 1. The MAPE values for the GM(1,N), GMVM(1,N), RGMVM(1,N), and FGMVM(1,N) models were 5.94%, 12.08%, 1.86%, and 4.50%, respectively. It is noteworthy that the accuracies of the FGMVM(1,N) and RGMVM(1,N) models were superior to those of the GM(1,N) and GMVM(1,N) models. Thus, the improved GMVM(1,N) model performed well in comparison with the other grey prediction models in this numerical example.

## 4 Empirical study

### 4.1 Collection of data and variables

According to the results of a validity test, the improved grey prediction model was applied to assess future CO<sub>2</sub> emissions in China by taking into account the bilateral FDI effect. In this paper, CO<sub>2</sub> emissions per unit GDP were chosen as characteristic variables of the system behavior. The IFDI, OFDI, and interaction item of both were used as the relevant variables.

Data on China’s CO<sub>2</sub> emissions were collected from the International Energy Association (IEA), and data on IFDI and OFDI were obtained using the World Bank Development Indicators. Table 2 shows the collected data. Raw data for 2008–2014 and 2015–2016 were reserved for model fitting and the ex-post test, respectively.

### 4.2 Empirical results

According to the modeling process mentioned above, the development and driving coefficients were estimated to be  $b_1 = 3.24 \times 10^{-8}$ ,  $b_2 = -3.25 \times 10^{-7}$ , and  $b_3 = 4.51 \times 10^{-12}$ . As explained by Ding et al. (2017), the development and driving coefficients  $b_i$  have

**Table 1** Prediction values and errors for numerical example

Actual	GM(1,N)		GMVM(1,N)		RGMVM(1,N)		FGMVM(1,N)		
	Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE	
$k = 1$	2.874	2.874	0.00	2.874	0.00	2.874	0.00	2.874	0.00
$k = 2$	3.278	2.769	15.52	3.283	0.17	3.278	0.00	3.086	5.85
$k = 3$	3.307	3.548	7.27	3.513	6.23	3.295	0.37	3.499	5.80
$k = 4$	3.390	3.534	4.26	4.071	20.10	3.252	4.08	3.198	5.66
$k = 5$	3.679	3.582	2.63	4.927	33.92	3.857	4.84	3.871	5.21
MAPE			5.94		12.08		1.86		4.50



**Table 2** Bilateral FDI and CO<sub>2</sub> emissions for the 2008–2016 period. *Source* IEA and World Bank Development Indicators

Year	CO <sub>2</sub>	IFDI	OFDI	IFDI×OFDI
2008	1.45	171.53	56.74	9733.27
2009	1.39	131.06	43.89	5752.09
2010	1.28	243.70	57.95	14123.49
2011	1.13	280.07	48.42	13561.28
2012	1.03	241.21	64.96	15670.07
2013	0.96	290.93	72.97	21229.30
2014	0.87	268.10	123.13	33010.69
2015	0.82	242.49	174.39	42287.88
2016	0.81	174.75	216.42	37820.08

their own meanings. Because  $b_1 > b_3 > 0 > b_2$ , it can be inferred that IFDI positively affected CO<sub>2</sub> emissions in China, which confirms the PHH. On the contrary, there was a negative relationship between OFDI and CO<sub>2</sub> emissions, which means that CO<sub>2</sub> emissions declined with increasing OFDI. It interesting to note that the effects of IFDI and OFDI on CO<sub>2</sub> emissions were opposing, but their interaction item led to increased CO<sub>2</sub> emissions. The coefficient of the interaction item indicates that the interaction effect of bilateral FDI intensified CO<sub>2</sub> emissions.

To examine its prediction accuracy, this model was compared with the GM(1,N), GMVM(1,N), RGMVM(1,N), and FGMVM(1,N) models. Table 3 summaries the model fitting and ex-post results for China's CO<sub>2</sub> emissions. The MAPE of the GM(1,N), RGMVM(1,N), GMVM(1,N), and FGMVM(1,N) models in relation to model fitting was 16.25%, 0.42%, 2.8% and 0.42%, respectively. The MAPE of the ex-post testing was 366.72%, 16.29%, 21.71%, and 15.14%, respectively. The prediction accuracies of the RGMVM(1,N), FGVM(1,N), and GMVM(1,N) models were thus much better than that of the GM(1,N) model for model fitting. At the same time, the FGMVM(1,N) model outperformed the GMVM(1,N), GM(1,N), and RGMVM(1,N) models in ex-post testing.

**Table 3** Prediction accuracies of the four models for CO<sub>2</sub> emissions

Year	Actual	GM(1,N)		GMVM(1,N)		RGMVM(1,N)		FGMVM(1,N)	
		Predicted	APE	Predicted	APE	Predicted	APE	Predicted	APE
2008	1.45	1.45	0.00	1.45	0.00	1.45	0.00	1.45	0.00
2009	1.39	1.33	4.65	1.40	0.33	1.39	0.00	1.39	0.12
2010	1.28	1.58	23.84	1.26	1.04	1.27	0.19	1.28	0.06
2011	1.13	1.22	7.54	1.16	2.41	1.14	0.54	1.14	0.39
2012	1.03	1.49	44.98	1.06	2.92	1.02	0.96	1.02	0.80
2013	0.96	0.74	22.47	1.01	5.20	0.96	0.14	0.95	0.32
2014	0.87	0.96	10.27	0.94	7.71	0.88	1.09	0.88	1.28
MAPE			16.25		2.80		0.42		0.42
2015	0.82	1.92	133.74	0.84	2.27	0.78	5.21	0.84	1.51
2016	0.81	5.66	599.71	0.56	30.32	0.50	38.21	0.58	28.77
MAPE			366.72		16.29		21.71		15.14

**Table 4** Prediction of bilateral FDI in 2017–2020

Year	IFDI	OFDI	IFDI × OFDI
2017	248.64	256.13	70779.23
2018	252.02	337.57	93912.97
2019	255.45	444.90	124607.82
2020	258.93	586.36	165335.09

**Table 5** Forecasting China's CO<sub>2</sub> emissions from 2017 to 2020

Year	2017	2018	2019	2020
CO <sub>2</sub>	0.68	0.64	0.65	0.78

Based on the results of the predictions, the proposed FGMVM(1,N) model could better predict China's CO<sub>2</sub> emissions than the other models. Therefore, it then used to forecast CO<sub>2</sub> emissions in China for the 2017–2020 period. However, CO<sub>2</sub> emissions can be forecasted only by predicting the relevant variables in advance: namely IFDI, OFDI, and the interaction item of bilateral FDI. The grey prediction GM(1,1) model was applied to predict the relevant variables from 2017 to 2020 as shown in Table 4.

The predicted values of the relevant variables were substituted into the FGMVM(1,N) model to predict China's CO<sub>2</sub> emissions. Predictions corresponding to the predicted IFDI, OFDI, and the interaction item of bilateral FDI were obtained correspondingly as shown in Table 5. It is clear that CO<sub>2</sub> emissions in China will fluctuate over the next four years.

### 4.3 Discussion and policy implications

This paper explored the relationship between CO<sub>2</sub> emissions, and IFDI, OFDI, and the interaction item of bilateral FDI in China based by developing a grey prediction model that incorporates the residual modification model into a grey multivariable Verhulst model. The model was used to forecast CO<sub>2</sub> emissions in China for the 2017–2020 period. The following conclusions can be drawn: first, IFDI and OFDI had opposite effects on CO<sub>2</sub> emissions. As far as the impact of bilateral FDI on CO<sub>2</sub> emissions is concerned, the development and driving coefficients indicated that IFDI reduced CO<sub>2</sub> emissions, whereas increasing OFDI reduced CO<sub>2</sub> emissions. The former result confirmed the PHH, which meant that attracting IFDI led to an increase in CO<sub>2</sub> emissions because developed countries transferred their highly polluting industries to China along with FDI. Thus, the effect of IFDI on CO<sub>2</sub> emissions was greater than its spillover effect on technological upgrade to improve the environment. The latter result suggested that implementing OFDI might have had a transferring effect on CO<sub>2</sub> emissions. It indirectly affected CO<sub>2</sub> emissions reduction by the reverse spillover effect of industrial restructuring and technological innovation. Moreover, the interaction effect of bilateral FDI aggravated CO<sub>2</sub> emissions. The interaction item of bilateral FDI had a positive effect on CO<sub>2</sub> emissions because of inconsistency and incompatibility in the simultaneous implementation of bilateral FDI. Finally, China needs to make considerable efforts for CO<sub>2</sub> emissions reduction. Because of the fluctuating predicted value of CO<sub>2</sub> emissions over the next few years, China still faces significant pressure to reduce carbon dioxide emissions. Nevertheless, it is noteworthy that according to the forecasting results

obtained in this paper, China can fulfill its goal of reducing emissions by 40–45% in 2020 compared with emissions in 2005.

The empirical results revealed the following policy implications: firstly, bilateral FDI should be selectively implemented. According to the PHH, the host country usually becomes a haven for highly polluting industries from foreign countries accompanied by IFDI. From the empirical results, it was found that the IFDI would increase CO<sub>2</sub> emissions in China. Therefore, the government should not only restrict IFDI for highly polluting and energy-intensive industries, but should also introduce IFDI to section of green economy, especially knowledge-intensive industries. Regarding OFDI, on the one hand, the government should prioritize transferring high-emission industries in accordance with the theory of marginal industry expansion. On the other hand, the government should encourage enterprises to move abroad and continue to expand OFDI, especially OFDI with the motivation for technological seeking. Secondly, the spillover effect of bilateral FDI should be considered important. A number of studies demonstrated that bilateral FDI has a spillover effect on the capacity for innovation, and research and development. More importantly, the improvements in innovation, and research and development promote productivity and energy efficiency, thereby reducing carbon dioxide emissions. In one respect, the government should encourage investment from multinational enterprises in energy conservation and environmental protection in the host country. In another respect, OFDI can generate the reverse spillover effect on technological upgrade in the home country through investment in countries with advanced technologies. Third, the trade-off of the interaction effect of bilateral FDI should be attended to. Although OFDI reduces CO<sub>2</sub> emissions, the interaction of bilateral FDI intensifies them. Therefore, when implementing the “bring in and go out” strategy, the government should coordinate the relationship between IFDI and OFDI and should implement the interaction effect of bilateral FDI on carbon dioxide emissions reduction.

## 5 Conclusions and future work

Due to the increase in bilateral FDI, the effects of IFDI and OFDI on CO<sub>2</sub> emissions have emerged as important issues in China. Because of the different effects of bilateral FDI on CO<sub>2</sub> emissions, this paper explored the influences of their interaction on CO<sub>2</sub> emissions as well as their nonlinear effects on CO<sub>2</sub> emissions. Therefore, the accurate prediction of CO<sub>2</sub> emissions by considering the effects of bilateral FDI can help formulate a coherent government policy on the subject. We proposed a grey multivariable Verhulst model (GMVM) to forecast CO<sub>2</sub> emissions in China by taking into account bilateral FDI effect. The Fourier series and GM(1,1) model were selected as the residual modification model, integrated with the GVM(1,N) model, to make the predictions more accurate. Our results showed that the improved GMVM more accurately described the nonlinear correlation of CO<sub>2</sub> emissions with bilateral FDI. Thus, the accuracy of forecasting using sequences of the relevant data was improved.

The grey multivariable Verhulst model, which used the residual modification model with the assistance of the Fourier series (FGVM(1,N) model), had the smallest MAPE, which indicates the highest prediction accuracy. Therefore, the FGVM(1,N) model was applied to forecast China's CO<sub>2</sub> emissions for the 2017–2020 period. In general, its prediction accuracy was excellent and the results were satisfactory. This shows that the improved GMVM is effective to forecast CO<sub>2</sub> emissions. According to the results, China

still faces severe pressure to reduce emissions due to fluctuations in CO<sub>2</sub> emissions in the future. Therefore, the government should implement bilateral FDI selectively and should pay attention to its spillover effect on the capacity for innovation, and research and development to promote carbon dioxide emissions reduction.

All empirical studies showed that the improved GVM(1,N) model, with a prediction accuracy higher than the other models, was applicable to the prediction of CO<sub>2</sub> emissions in China. However, it still has some limitations. The accuracy of the FGVM(1,N) model was better than that of the RGVM(1,N) model, which indicates better performance of the integrated Fourier series and GVM(1,N) model than that of GM(1,1). This was because the Fourier series better reflected the nonlinear characteristics of residuals than the GM(1,1) model. Hence, there are some other approaches available to combine with GVM(1,N) to achieve better prediction performance, such as by using the Markov chain and neural networks, which deserve further research. Our subsequent studies will focus on implementing big data to reduce the error in data fluctuation.

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### Appendix 1: Using GM(1,1) model as residual modification approach

Residual modification using the GM(1,1) model is modeled as follows:

*Step 1* Establish a GVM(1,N) model for  $X_1^{(0)}$ . Then, the residual  $\epsilon_k^{(0)} = (\epsilon_2^{(0)}, \epsilon_3^{(0)}, \dots, \epsilon_n^{(0)})$  can be generated.

*Step 2* Transform the residual sequence into a new sequence by the accumulated generating operation (AGO). A new sequence,  $\epsilon_k^{(1)} = (\epsilon_2^{(1)}, \epsilon_3^{(1)}, \dots, \epsilon_n^{(1)})$  is generated by

$$\epsilon_k^{(1)} = \sum_{j=1}^k \epsilon_j^{(0)}, \quad k = 2, 3, \dots, n \tag{13}$$

and  $\epsilon_2^{(1)}, \epsilon_3^{(1)}, \dots, x_n^{(1)}$  can be then assessed by a first-order differential equation:

$$\frac{d\epsilon^{(1)}}{dt} + a_\epsilon \epsilon^{(1)} = b_\epsilon \tag{14}$$

where  $a_\epsilon$  and  $b_\epsilon$  are a developing coefficient and a control variable, respectively. The predicted value,  $\hat{\epsilon}_k^{(1)}$ , of  $\epsilon_k^{(1)}$  can be obtained by solving the differential equation at  $\epsilon_2^{(1)} = \epsilon_2^{(0)}$  as initial condition:

$$\hat{\epsilon}_k^{(1)} = (\epsilon_2^{(0)} - \frac{b_\epsilon}{a_\epsilon})e^{-a_\epsilon(k-1)} + \frac{b_\epsilon}{a_\epsilon}, k = 3, 4, \dots, n. \tag{15}$$

Step 3 Use the ordinary least squares methods (OLS) to estimate  $a_\epsilon$  and  $b_\epsilon$ :

$$[a_\epsilon, b_\epsilon]^T = (B^T B)^{-1} B^T y \tag{16}$$

where

$$B = \begin{bmatrix} -z_2^{(1)} & 1 \\ -z_3^{(1)} & 1 \\ \vdots & \vdots \\ -z_n^{(1)} & 1 \end{bmatrix} \tag{17}$$

$$z_k^{(1)} = \frac{1}{2}(\epsilon_k^{(1)} + \epsilon_{k-1}^{(1)}) \tag{18}$$

$$y = [\epsilon_3^{(0)}, \epsilon_4^{(0)}, \dots, \epsilon_n^{(0)}]^T \tag{19}$$

where  $z_k^{(1)}$  is the background value.

Step 4 Perform the inverse accumulated generating operating (IAGO). Using the IAGO, the predicted value or  $\hat{\epsilon}_k^{(0)}$  is

$$\hat{\epsilon}_k^{(0)} = \hat{\epsilon}_k^{(1)} - \hat{\epsilon}_{k-1}^{(1)}, k = 2, 3, \dots, n. \tag{20}$$

Therefore,

$$\hat{\epsilon}_k^{(0)} = (1 - e^{a_\epsilon}) \left[ \epsilon_1^{(0)} - \frac{b_\epsilon}{a_\epsilon} \right] e^{-a_\epsilon(k-1)}, k = 2, 3, \dots, n \tag{21}$$

while  $\hat{\epsilon}_2^{(1)} = \epsilon_2^{(0)}$ .

## Appendix 2: Using Fourier series as residual modification approach

Residual modification using Fourier series

Step 1 The residual sequence,  $\epsilon_k^{(0)} = (\epsilon_2^{(0)}, \epsilon_3^{(0)}, \dots, \epsilon_n^{(0)})$ , is generated by the GVM(1,N) model.

Step 2 Expressed as a Fourier series,  $\epsilon_k^{(0)}$  can be rewritten as:

$$\epsilon_k^{(0)} = \frac{1}{2}a_0 + \sum_{i=1}^F \left[ a_i \cos\left(\frac{2\pi i}{n-1}k\right) + b_i \sin\left(\frac{2\pi i}{n-1}k\right) \right], k = 2, 3, \dots, n \tag{22}$$

where  $F = (n - 1)/2 - 1$  is the minimum deployment frequency of the Fourier series and can be expressed using only integers. Thus, the residual series can be rewritten as:

$$\epsilon^{(0)} = PC \tag{23}$$

where





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