Prediction on transaction amounts of China's CBEC with improved GM (1, 1) models based on the principle of new information priority

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Abstract

Benefited by e-commerce activities and information technology development, cross-border e-commerce (CBEC) has experienced rapid growth and attracted much research attention. This study takes China's CBEC as a typical research object and intends to forecast its future development trend based on an exploration of its dynamic changing rules as a whole. The data set of transaction amounts of China's CBEC from 2008 to 2018 was used in the modeling processes of improved grey models (GM) (1,1) proposed in this study, after which forecast results on the development of China's CBEC from 2019 to 2020 were achieved. The experimental results reveal that, introducing the principle of new information priority to the improvement of grey models indeed works when forecasting a newly-emerging and vulnerable system like CBEC. Finally, it is predicted that China's CBEC promises to continue to grow in the near future.

Keywords CBEC · Reversed GM (1,1) model · Renewal GM (1,1) model · New information priority · Forecast

1 Introduction

Cross-border e-commerce (CBEC) refers to an international trade activity in which two individuals or enterprises in different countries make transactions on e-commerce platforms and deliver goods through cross-border logistics [1, 2]. The emergence and development of CBEC do count for the overall development of international trade activities and countries' economies. In the last decade, it has experienced tremendous growth. Nielsen's online shopper trend study showed that the proportion of customers who had recently made a cross-border purchase

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reached 67% in 2017 compared with 34% in 2015 [3]. Taking China as an example, iiMedia Research [4] reported that the total transaction volume of China's CBEC reached RMB 7.6 trillion in 2017 and RMB 9.1 trillion in 2018, which was quite a rapid annual growth.

The globalization of e-commerce and the development of information technology and logistics have drawn the attention of many countries to CBEC [5, 6]. For example, in European online retail markets, CBEC is the key to facilitating online transactions [5]. In addition, China pays particular attention to CBEC and has enacted various policies to facilitate its transactions among different countries, which makes CBEC become a crucial force in the Belt and Road Initiative (BRI). For example, State Taxation Administration [7] has launched tax refunds and exemption policies to inspire Chinese companies to export products to other countries. Further, China's State Council has enacted a series of policies to incubate CBEC platforms and to encourage companies to expand their market overseas and establish overseas retail systems [8]. Given these realities, it's quite important to capture the dynamic changes of CBEC so that relevant policies and actions could be adjusted accordingly in time to further encourage its development.

Capturing its dynamic changes calls for a specific method to measure the development status of CBEC in different time periods and to grasp its future development trend in advance. However, there are mainly two challenges involved in accurately measuring and forecasting CBEC's development. First, since CBEC is a newly emerging industry featured with a late start and a rapid development speed, there is not enough data available for researching its internal relationships, thus establishing a completely quantifiable influencing factor system is nearly impossible till now. Second, the nature of CBEC makes itself vulnerable to occasional factors or sudden events such as the China-United States (US) trade war which began in March 2018, along with the coronavirus disease 2019 (COVID-19) which began in January 2020. This characteristic will be more or less reflected in its irregular changes among the same time interval, which often makes it difficult to accurately measure or forecast the future development of CBEC based on some classical forecasting models. In conclusion, these two challenges imply that the CBEC system can be treated as a grey system due to its part of unknowable information internally and the recent information conveyed by the latest events does have more value for its future predictions, which can be seen as the principle of new information priority.

To address these challenges, this study takes China's CBEC as a typical research object and intends to forecast its overall development based on mining information hidden in its dynamic changes. As for the selection of forecasting models, improved grey models (GM) (1,1) based on the principle of new information priority will be quite suitable.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 demonstrates modeling methods and presents prediction models that apply grey system theory, including the traditional GM (1,1) model and two improved GM (1,1) models based on the principle of new information priority. Section 4 explains the adaptability of the model and the sample. In addition, the experimental results generated by three grey models are compared with those of two time series analysis models in Sect. 4, and a prediction for China's CBEC is then

made. Section 5 presents conclusions and Sect. 6 summarizes research limitations and future research directions.

2 Literature review

2.1 CBEC in China

China's CBEC emerged in 1997. Some of early companies ran online shops on eBay that sold popular electronic products such as MP3 and MP4 players. In general, the development course of CBEC in China can be divided into three stages, which are outlined below.

Stage 1, 1997–2007: During this period, Alibaba International Station was established in Hangzhou and Made-in-China.com was established in Nanjing. Both of these companies are still successful business-to-business (B2B)-based CBEC companies. This stage can be considered as the budding stage of CBEC in China.

Stage 2, 2008–2013: As a result of the rapid global development of information technology and the increasing rate of Internet penetration, the infrastructure of CBEC in China improved significantly, as did its service quality. An increasing number of CBEC platforms began to conduct business-to-consumer (B2C) business in this stage. For instance, LightintheBox and AliExpress were launched in 2007 and 2009 respectively. This stage can be considered as the developing stage of CBEC in China.

Stage 3, 2014–present: China's BRI, which was officially launched in 2015, is a landmark event for CBEC. The BRI seeks to improve infrastructure construction and deliver new technologies to countries beyond the immediate borders of China. The launch of the BRI provides benefits to economies of both China and the rest of the world—especially to countries along the BRI [9]. The policy opens a new window for Chinese CBEC companies to go global. The demand for cross-border products has increased dramatically during this period. According to ChinaIRN [10], there were more than 23,265 CBEC enterprises in China at the end of 2019. Successful representative B2C-based CBEC companies and platforms include Tmall International and NetEase Kaola. In this stage, CBEC is deemed to be approaching maturity.

In view of the extraordinary performance of China's CBEC in all aspects during the last two decades, its dynamic changes and future development are quite worthy of in-depth investigation.

2.2 Research in CBEC

The rapid development of CBEC has attracted attention of researchers. Studies that focused on issues related to CBEC can be classified into different categories based on the research topics.

First, like conventional e-commerce research, an important research focus within the field of CBEC is behaviors of buyers and sellers based on survey data and online

reviews [2, 11, 12]. For instance, Cui et al. [13] focused on understanding consumer intentions toward cross-border m-commerce usage with an integrated model, and they noted the importance of consumer satisfaction to both trust and commitment. Mou et al. [14] noted that sellers were most concerned about commission, product auditing and communication between sellers and buyers while buyers mentioned topics about the return and refund, product tracking and product descriptions most often.

Another stream of research has focused on supply chain and logistics problems in CBEC [15–17]. For instance, Wang et al. [18] delineated how CBEC firms could generate supply chain service capabilities to improve the quality of the supply chain relationship between e-tailors and other platform users. Niu et al. [3] thought that when customers purchased goods by way of CBEC, the logistics service quality was one of the issues they cared most about.

Other studies have focused on the requirements of CBEC talents [19], the customs classification process for CBEC products [20], early-mover advantages for B2B-based CBEC portals [21], and drivers of and impediments to CBEC [22].

Generally, to date, there has been both qualitative and quantitative research on CBEC, employing diverse research methods and a relatively wide range of research subjects as discussed above. From separate, internal perspectives of CBEC such as supply chains, logistics, talents, laws, etc., scholars have made fruitful achievements in exploring all kinds of problems during the development course of CBEC, and thus corresponding countermeasures are also proposed to further CBEC's development. However, the existing research lacks consideration of the CBEC system from an overall perspective and fails to capture the information hidden in its dynamic changes as a whole system. In fact, only when the future development trend of CBEC as a whole is grasped in advance according to its changing rules, can specific measures with regard to logistics, laws, credit, etc., be eventually put in place in a targeted manner. Therefore, in order to fill this research gap, this study devotes to seeing CBEC as a whole system, exploring its dynamic changes and investigating its future development trend based on suitable forecasting models by taking China as a typical example.

2.3 Research in grey predictions

Grey system theory was first proposed by Deng [23]. In reality, there are always known information and unknown information within an object or a system. In control theory, the shade of the color is often used to describe the clarity degree of information. For example, “white” refers to known information while “black” refers to unknown information. In this way, “grey” means a mixture of known and unknown information, which exactly explains what a grey system is indeed. Grey system theory takes a grey system as its research object and aims to provide a correct description of its operational behavior by generating and developing a small amount of known information, and to make a quantitative prediction of its future changes [24]. The main advantage of using grey system theory to make predictions

is that it can generate satisfactory results with a relatively small quantity of data, which can help to solve the problem of a lack of data [25].

As a modeling method, grey system theory has been widely employed in research fields such as energy [26], transportation [27], economy [28], electricity [29], population [30], etc. Grey prediction is a basic and the most important part of grey system theory. The most classic grey prediction model is GM (1,1) model [24]. As a result of the deepening research on grey system theory, researchers have conducted an increasing amount of research and made improvements to grey models to eliminate deviations and improve the prediction accuracy. For instance, Gong et al. [31] combined the grey model with the Markov prediction model. As a result, the grey model revealed the overall development trend, while the Markov prediction model processed the dynamic data, which allowed the fitting accuracy to be improved. Ji et al. [32] proposed an unbiased grey model that could eliminate the inherent deviation of the traditional GM (1,1) model, thus improving the modeling speed. In addition, one important idea of improving grey prediction models is that new information takes precedence [33]. Li et al. [34] optimized the traditional GM (1,1) model based on new information priority in consideration of the difference in information value between old and new data, and they proved its superiority in terms of prediction accuracy.

As for the selection of specific models for forecasting the future development trend of CBEC which has been always influenced by many unknown, complex external factors, it is appropriate to introduce the principle of new information priority to grey prediction models. Therefore, this study contributes to CBEC research in a way of exploring the superiority of forecasting models combining grey system theory with the improvement idea of new information priority for CBEC predictions. It is an initial exploration of a new research direction and can also provide a reference for future prediction research within the field of CBEC.

3 Modeling methods

3.1 Traditional GM (1,1) model

There are known and unknown information within a system. For known information, there is some relation among them that can be internally explored based on real data. Therefore, grey models process the original data to determine the law of system changes by identifying known information contained in the system itself. The data sequences with strong regularity are then generated, and the corresponding differential equation models are thus established, which explains how grey models can be used to forecast the future development trend of objects [24].

It is assumed that there is an original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, and where $x^{(0)}(k) \geq 0$, $k = 1, 2, \dots, n$, a traditional GM (1,1) model could then be established, as shown in the following steps [35].

Step (1): Calculate $X^{(1)}$, the 1-accumulated generating operation (1-AGO) sequence of $X^{(0)}$ given by

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)) \quad (1)$$

where

$$x^{(1)}(k) = \sum_1^k x^{(0)}(i), \quad k = 1, 2, \dots, n \quad (2)$$

Step (2): Calculate $Z^{(1)}$, the mean-generated sequence of consecutive neighbors of $X^{(1)}$ given by

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

where

$$z^{(1)}(k) = \frac{1}{2}(x^{(1)}(k) + x^{(1)}(k-1)), \quad k = 2, 3, \dots, n \quad (4)$$

Then, a grey differential equation is determined as

$$x^{(0)}(k) + ax^{(1)}(k) = b \quad (5)$$

where, a and b are two parameters.

Step (3): Calculate parameters a, b

The parameter vector $\hat{a} = [a, b]^T$ can be estimated using the least squares method (LSM), which indicates that

$$\hat{a} = (B^T B)^{-1} B^T Y \quad (6)$$

where

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \quad (7)$$

In addition,

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \quad (8)$$

is called a “whitenization equation” of the grey differential equation Eq. (5), also known as the shadow equation.

Step (4): Determine the time-response function of the whitenization equation given by

$$\hat{x}^{(1)}(k) = \left(x^{(0)}(1) - \frac{b}{a} \right) e^{-a(k-1)} + \frac{b}{a}, \quad k = 1, 2, \dots, n \quad (9)$$

Step (5): Calculate the corresponding model-simulated sequence given by

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \quad k = 2, 3, \dots, n \quad (10)$$

$$\hat{x}^{(0)}(1) = x^{(0)}(1) \quad (11)$$

3.2 Improved GM (1,1) models based on new information priority

Given the difficulties involved in forecasting the future development of CBEC, we believe that grey models would be the best tool. For newly emerging phenomena that are characterized by rapid development and high sensitivities to external conditions, "new information" has more value than "old information". Thus, assigning a greater weight to new information is believed to improve the efficiency and the prediction accuracy of grey models. Therefore, improved GM (1,1) models based on the principle of new information priority for forecasting CBEC's development are proposed in this study.

3.2.1 Reversed GM (1,1) model

Based on the principle of new information priority, the first improved GM (1,1) model that this study applied was first proposed by Dang et al. [35]. In this model, the n th component of $X^{(1)}$ is chosen as the starting condition of the time-response function.

It is assumed that there is an original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, and where $x^{(0)}(k) \geq 0$, $k = 1, 2, \dots, n$.

Steps (1) to (3) are the same as Steps (1) to (3) in the traditional GM (1,1) modeling (presented above).

Step (4): Determine the time-response function of the whitenization equation given by

$$\hat{x}^{(1)}(k) = \left(x^{(1)}(n) - \frac{b}{a} \right) e^{-a(k-n)} + \frac{b}{a}, \quad k = 1, 2, \dots, n \quad (12)$$

Step (5): Calculate the corresponding model-simulated sequence given by

$$\hat{x}^{(0)}(k) = \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), \quad k = 2, 3, \dots, n \quad (13)$$

$$\hat{x}^{(0)}(1) = \hat{x}^{(1)}(1) \quad (14)$$

Among the modeling equations, Eq. (12) is a transformation of Eq. (9) and it just presents the most important improvement based on the principle of new information priority. When comparing Eq. (12) with Eq. (9), the main difference is that Eq. (12) takes $x^{(1)}(n)$ as the initial value, while Eq. (9) takes $x^{(0)}(1)$ as the initial value. Therefore, when calculating the corresponding model-simulated sequence in Step (5), $\hat{x}^{(0)}(1)$ is the same as $x^{(0)}(1)$ in the original sequence for Eq. (9), but $\hat{x}^{(1)}(n)$ is the same as $x^{(1)}(n)$ in the 1-AGO sequence for Eq. (12). That is, new information is allocated a greater weight with the initial value reversed. Based on the improvement

idea of reversing the initial value, we rename the first improved GM (1,1) model based on new information priority as the “reversed GM (1,1) model”.

In addition, if we take $x^{(0)}(1)$ as the initial value, the fitted values generated by the model are independent of $x^{(0)}(1)$ in the original sequence. Nevertheless, the reversed GM (1,1) model takes $x^{(1)}(n)$, which is accumulated from the original sequence, as the initial value. Hence, the existing known information can be exploited to the greatest extent. Moreover, this improvement is exactly in accordance with the minimum information principle which means fully exploiting and using available “minimum information” in grey system theory.

3.2.2 Renewal GM (1,1) model

There is another improved GM (1,1) model based on new information priority named the “renewal GM (1,1) model” [36]. Its principle is to place new information $x^{(0)}(n+1)$ into the original sequence and, at the same time, remove the oldest information $x^{(0)}(1)$, thus establishing a new original sequence $X^{(0)} = (x^{(0)}(2), x^{(0)}(3), \dots, x^{(0)}(n+1))$. The rest of the procedures for the renewal GM (1,1) model repeat the modeling steps described above for the traditional GM (1,1) model. Forecasting will ultimately be achieved by repeating a certain number of times throughout the whole operation cycle of removing old information from and adding new information to the original sequence. Its calculation process is more complex than the reversed GM (1,1) model due to repeated operations of deleting and adding information.

3.3 Features of models

The assumptions, applicabilities, advantages, and disadvantages of these three grey models are compared and summarized in Table 1.

3.4 Verification of accuracy

After establishing a prediction model, its fitting accuracy, which actually reflects the prediction accuracy of this model, must be tested by comparing its fitted values with actual values. Only when the prediction accuracy of a model has been confirmed good enough can this model be used for predictions. This study uses two common tests of prediction accuracy—the relative error method and the ratio of mean square deviations C-test index—to test the fitting accuracy of prediction models. These two tests are presented below.

It is assumed that there is an original sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n))$, and its corresponding model-simulated sequence is $\hat{X}^{(0)} = (\hat{x}^{(0)}(1), \hat{x}^{(0)}(2), \dots, \hat{x}^{(0)}(n))$. Then the sequence of errors is

$$\varepsilon^{(0)} = (\varepsilon(1), \varepsilon(2), \dots, \varepsilon(n)) = x^{(0)}(1) - (\hat{x}^{(0)}(1), x^{(0)}(2) - \hat{x}^{(0)}(2), \dots, x^{(0)}(n) - \hat{x}^{(0)}(n)) \quad (15)$$

And the sequence of relative errors is

Table 1 Features of the traditional and two improved GM (1,1) models

Feature	Traditional GM (1,1) model	Based on new information priority	
		Reversed GM (1,1) model	Renewal GM (1,1) model
Assumption	It can predict the future development of a grey system by exploring the law of known information internally	Based on the traditional GM (1,1) model, the principle of new information priority is also considered, that is, "new information" is much more important than "old information"	
Applicability	It can generate satisfactory results using a relatively small quantity of data, which can help to solve the problem of a lack of data	Apart from solving the problem of a lack of data, it is suitable for processing a grey system featured with a rapid development speed and a high sensitivity to external changes	
Advantage	It has the simplest modeling process and can meet the basic prediction needs of grey systems in most cases	It takes the principle of new information priority into consideration, which broadens the use of the traditional GM (1,1) model in different fields and complex circumstances	
Disadvantage	It is the most basic GM (1,1) model but always fails to process complex conditions	The modeling process may be complex	It always has the longest and the most complex modeling process

$$\Delta = (\Delta_1, \Delta_2, \dots, \Delta_n) = \left(\left| \frac{\varepsilon(1)}{x^{(0)}(1)} \right|, \left| \frac{\varepsilon(2)}{x^{(0)}(2)} \right|, \dots, \left| \frac{\varepsilon(n)}{x^{(0)}(n)} \right| \right) \quad (16)$$

$$\bar{\Delta} = \frac{1}{n} \sum_{k=1}^n \Delta_k \quad (17)$$

For $k = 1, 2, \dots, n$, $\left| \frac{\varepsilon(k)}{x^{(0)}(k)} \right|$ is called the relative simulation error at point k , while $\bar{\Delta}$ is called the mean relative simulation error.

$$p_k = 1 - \Delta_k \quad (18)$$

$$p = 1 - \bar{\Delta} \quad (19)$$

Similarly, for $k = 1, 2, \dots, n$, p_k is called the filtering accuracy, while p is called the mean relative fitting accuracy, which indicates the prediction accuracy of a prediction model.

$$S_1 = \sqrt{\frac{\sum_{k=1}^n (\varepsilon(k) - \bar{\varepsilon})^2}{n-1}}, \bar{\varepsilon} = \frac{\sum_{k=1}^n \varepsilon(k)}{n} \quad (20)$$

$$S_2 = \sqrt{\frac{\sum_{k=1}^n (x^{(0)}(k) - \bar{x})^2}{n-1}}, \bar{x} = \frac{\sum_{k=1}^n x^{(0)}(k)}{n} \quad (21)$$

$$C = \frac{S_1}{S_2} \quad (22)$$

where $\bar{\varepsilon}$ is the mean error and S_1 is the standard deviation of errors, while $\bar{x}$ is the mean of the original sequence $X^{(0)}$ and S_2 is the standard deviation of $X^{(0)}$. In addition, C is called the ratio of mean square deviations. When a model is equipped with a smaller mean relative simulation error, a larger mean relative fitting accuracy and a smaller ratio of mean square deviations, it is often believed to have a better forecasting effect [24].

Based on these test indexes, the reference for the level of prediction accuracy of grey models is presented in Table 2 [25].

Table 2 Reference table for the level of prediction accuracy of grey models

Accuracy	$\Delta_k(\%)$	$p(\%)$	C
First level (excellent)	1	≥ 95	≤ 0.35
Second level (qualified)	5	$80 \leq p \leq 95$	$0.35 < C \leq 0.5$
Third level (barely qualified)	10	$70 \leq p \leq 80$	$0.5 < C \leq 0.65$
Fourth level (unqualified)	20	< 70	> 0.65

4 Forecasting the transaction amounts of CBEC in China

4.1 Data selection

The total import and export transaction amounts of CBEC in China from 2008 to 2018 were selected as an indicator to measure the overall development status of China's CBEC. Among this data set, data from 2008 to 2017 were used for modeling while data in 2018 was used for verification, then transaction amounts of China's CBEC from 2019 to 2020 would be forecasted. This data set was chosen for three reasons. First, China's CBEC entered a period of rapid development in 2008. Second, considering the basic principle of new information priority, information from more than ten years ago always has a lower value for future predictions, and data closer to the forecast period has a more positive effect on the prediction accuracy of a model. Third, the following verification experiment would allow an additional comparison between the actual value and the forecast result generated by three grey models for 2018, which could further verify the prediction accuracy of models and to some degree identify how the influence brought by trade events happened in 2018 (e.g., the China-US trade war) had worked on the development of China's CBEC that year.

The specific data are shown in Fig. 1, which was plotted with the tool of Origin 2018. All the data were collected from www.ebrun.com and released by iiMedia Research.

According to Fig. 1, from 2008 to 2018, the total transaction amounts of CBEC in China show a significant increasing trend, and this trend can approximate the exponential trend line.

Fig. 1 Transaction amounts of China's CBEC from 2008 to 2018

As seen in Fig. 1, when modeling with data from 2008 to 2017, the original sequence is $X^{(0)} = \{0.80, 0.90, 1.20, 1.60, 2.00, 2.70, 3.75, 4.80, 6.30, 7.60\}$. Thus, the 1-AGO sequence $X^{(1)} = \{0.80, 1.70, 2.90, 4.50, 6.50, 9.20, 12.95, 17.75, 24.05, 31.65\}$ is established.

Before the modeling analysis, a check of quasi-smoothness on $X^{(0)}$ and a check of law of quasi-exponentiality on $X^{(1)}$ were performed accordingly as presented below [25].

According to the quasi-smoothness check on $X^{(0)}$, from

$$\rho(k) = \frac{x^{(0)}(k)}{x^{(1)}(k-1)}, \quad k = 2, 3, \dots, n \quad (23)$$

it follows that $\rho_4 \approx 0.55$, $\rho(5) \approx 0.44 < 0.5$, $\rho(6), \rho(7), \dots, \rho(10) < 0.5$. Therefore, the condition of being quasi-smooth is satisfied when $k > 4$.

According to a check of law of quasi-exponentiality on $X^{(1)}$, from

$$\sigma^{(1)}(k) = \frac{x^{(1)}(k)}{x^{(1)}(k-1)}, \quad k = 2, 3, \dots, n \quad (24)$$

it follows that $\sigma^{(1)}(4) \approx 1.55$, $\sigma^{(1)}(5) \approx 1.44$, $\sigma^{(1)}(6) \approx 1.42, \dots, \sigma^{(1)}(10) \approx 1.32$. Thus, when $k > 4$, $\sigma^{(1)}(k) \in [1, 1.5]$, $\delta = 0.5$, it also satisfies the law of quasi-exponentiality. Therefore, it is feasible to establish a GM (1,1) model for the data set of China's CBEC import and export transaction amounts from 2008 to 2017.

4.2 Grey predictions on transaction amounts of China's CBEC

4.2.1 Traditional GM (1,1) model

The modeling process based on the traditional GM (1,1) model for transaction amounts of China's CBEC from 2008 to 2017 is as follows. The mean-generated sequence of consecutive neighbors is displayed as

$$Z^{(1)} = \{1.25, 2.30, 3.70, 5.50, 7.85, 11.075, 15.35, 20.90, 27.85\}$$

Then, the data matrix B , Y is established as

$$B = \begin{bmatrix} -1.25 & 1 \\ -2.30 & 1 \\ \vdots & \vdots \\ -27.85 & 1 \end{bmatrix}, Y = \begin{bmatrix} 0.90 \\ 1.20 \\ \vdots \\ 7.60 \end{bmatrix}$$

Therefore, the parameter vector $\hat{a} = [a, b]^T = (B^T B)^{-1} B^T Y = \begin{bmatrix} -0.2594 \\ 0.6669 \end{bmatrix}$, which indicates that parameter $a = -0.2594$ and parameter $b = 0.6669$.

According to Eq. (9), the time-response function of the whitenization equation is also determined as

$$\hat{x}^{(1)}(k) = 3.3707e^{0.2594(k-1)} - 2.5707, \quad k = 1, 2, \dots, 10$$

Based on Eqs. (10) and (11), the fitted values of transaction amounts of China's CBEC from 2008 to 2017, which are generated by the traditional GM (1,1) model, can be obtained.

Based on Eqs. (17) and (19), the mean relative simulation error is $\bar{\Delta} = 5.32\%$ and the mean relative fitting accuracy is $p = 94.68\%$. As seen in Table 2, the prediction accuracy of the traditional GM (1,1) model for forecasting transaction amounts of China's CBEC is at the second level (qualified), which demonstrates that it has a relatively good forecasting effect.

4.2.2 Reversed GM (1,1) model

For the reversed GM (1,1) model based on new information priority, the time-response function of the whitenization equation is determined as

$$\hat{x}^{(1)}(k) = 34.2207e^{0.2594(k-10)} - 2.5707, \quad k = 1, 2, \dots, 10$$

Based on Eqs. (10) and (11), the fitted values of transaction amounts of China's CBEC from 2008 to 2017 generated by the reversed GM (1,1) model are also obtained, as seen in Table 3.

Based on Eqs. (17) and (19), the mean relative simulation error is $\bar{\Delta} = 4.92\%$ and the mean relative fitting accuracy is $p = 95.08\%$. As shown in Table 2, the prediction accuracy of the reversed GM (1,1) model for forecasting transaction amounts of China's CBEC is at the first level (excellent).

4.2.3 Renewal GM (1,1) model

The essence of the renewal GM (1,1) model is to replace old information with new information. To predict the transaction amounts of China's CBEC from 2019 to 2020, it is important to repeat the process of adding new information and removing old information twice based on the traditional GM (1,1) modeling. After each process is repeated, GM (1,1) modeling is performed twice separately, thereby establishing two models: renewal GM (1,1) model I and renewal GM (1,1) model II. The entire process is collectively referred to as the renewal GM (1,1) model.

First, the forecast value for 2018 generated by the traditional GM (1,1) model should be added to the original sequence to replace the RMB 0.8 trillion in 2008 according to the modeling principle of the renewal GM (1,1) model. As a result, a new original sequence is transformed as $X^{(0)} = \{0.90, 1.20, 1.60, 2.00, 2.70, 3.75, 4.80, 6.30, 7.60, 10.31\}$, and a new time-response function of the whitenization equation is determined as $\hat{x}^{(1)}(k) = 4.2963e^{0.2603(k-2)} - 3.3963$, $k = 2, 3, \dots, 11$. Thus, the renewal GM (1,1) model I is established, and the forecast value for 2019 generated by the renewal GM (1,1) model I is thus obtained.

Second, after removing the RMB 0.9 trillion in 2009 out of the original sequence, another new time-response function of the whitenization equation

Table 3 Comparison of fitted values of transaction amounts of China's CBEC from 2008 to 2017 generated by each model

Year	A.V	Time series analysis				Traditional GM (1,1) model		Based on new information priority			
								Reversed GM (1,1) model		Renewal GM (1,1) model	
		Double moving average model ($N=2$)		Double exponential smoothing model ($a=0.99$)							
		F.V	$\Delta_k(\%)$	F.V	$\Delta_k(\%)$	F.V	$\Delta_k(\%)$	F.V	$\Delta_k(\%)$	F.V	$\Delta_k(\%)$
2008	0.80	0.85	–	0.85	–	0.80	–	0.74	7.19	0.80	–
2009	0.90	0.85	–	0.85	5.56	1.00	10.93	0.98	9.04	0.90	–
2010	1.20	0.85	–	0.95	20.92	1.29	7.84	1.27	6.00	1.20	–
2011	1.60	1.35	15.63	1.49	6.56	1.68	4.84	1.65	3.05	1.66	3.85
2012	2.00	1.93	3.75	2.00	0.10	2.17	8.72	2.14	6.86	2.15	7.64
2013	2.70	2.40	11.11	2.40	11.11	2.82	4.38	2.77	2.60	2.79	3.31
2014	3.75	3.18	15.33	3.39	9.49	3.65	2.58	3.59	4.25	3.61	3.63
2015	4.80	4.54	5.47	4.79	0.15	4.74	1.35	4.65	3.03	4.68	2.45
2016	6.30	5.85	7.14	5.85	7.14	6.14	2.58	6.03	4.24	6.07	3.70
2017	7.60	7.46	1.81	7.79	2.51	7.96	4.68	7.82	2.89	7.86	3.43
$\bar{\Delta}(\%)$		8.61		7.06		5.32		4.92		4.00	
$p(\%)$		91.39		92.94		94.68		95.08		96.00	
C		0.0724		0.0860		0.0657		0.0637		0.0744	

¹A.V. refers to the actual value (RMB/trillion); F.V. refers to the fitted value (RMB/trillion)

²For double moving average model, the fitted values from 2008 to 2010 were calculated originally based on the mean value of actual values for 2008 and 2009 and thus $N=2$, which was confirmed by advance trials to have a better fitting accuracy than $N=3, 4, 5$, etc.

³For double exponential smoothing model, the fitted value for 2008 was calculated originally based on the mean value of actual values for 2008 and 2009 and in order to maximize the implementation of new information priority, new data was given as much weight as possible, that is, $a=0.99$, which was also confirmed by advance trials to have a better fitting accuracy than $a=0.95, 0.90, 0.80$, etc.

is determined as $\hat{x}^{(1)}(k) = 5.6197e^{0.2603(k-3)} - 3.3963, k = 3, 4, \dots, 12$. Thus, the renewal GM (1,1) model II is established based on the forecast value for 2019 generated by the renewal GM (1,1) model I. The fitted values of transaction amounts of China's CBEC from 2011 to 2017 generated by the renewal GM (1,1) model II are thus obtained, which are just those generated by the renewal GM (1,1) model.

Based on Eq. (17) and Eq. (19), if the renewal GM (1,1) model is applied, the mean relative simulation error is $\bar{\Delta} = 4.00\%$ and the mean relative fitting accuracy is $p = 96.00\%$. As shown in Table 2, the prediction accuracy of the renewal GM (1,1) model is at the first level (excellent) as well, which indicates that its forecasting effect is highly accurate.

4.3 Comparison and analysis

To enable more intuitive observations of the superiority of forecasting effects of the traditional and two improved GM (1,1) models, the fitted values generated by the time series analysis models are added to the comparison.

Regarding the time series analysis, we select two common and typical time series analysis models, that is, double moving average model and double exponential smoothing model. These two models are designed for analyzing and forecasting time series data equipped with long-term trends. Obviously, among the general time series analysis models, these two models are the most suitable tools since the transaction amounts of China's CBEC from 2008 to 2017 have shown such a clear increasing trend. In addition, there is also an idea of new information priority hidden between their differences, that is, double moving average model assumes that only the recent states of things within N periods would influence their future developments but it puts the same weight on these recent N -period data, while double exponential smoothing model assumes that the states of things in each period would have impacts on their future developments but the degree of impacts is always different, which means that the impact of recent data is greater than that of older data [37]. In common sense, the latter model is an improvement of the former one based on the principle of new information priority, either. Generally, differences in forecasting effects between the time series analysis and grey system theory could be captured and whether considering the principle of new information priority is of value could be further identified in this comparison (see Table 3).

As shown in Table 3, the fitted values generated by two time series analysis models deviate significantly from the actual values. Moreover, more than 10% of the relative simulation errors appears for several times in the fitted results separately generated by these two time series analysis models. That's to say, when the data set of transaction amounts of China's CBEC from 2008 to 2017 is used for modeling, the time series analysis performs much worse than grey system theory. However, the higher mean relative fitting accuracy of double exponential smoothing model than that of double moving average model proves that the idea of new information priority also counts in improving time series analysis models.

Among three grey models, it can be concluded that the two improved GM (1,1) models, which are based on the principle of new information priority, have higher mean relative fitting accuracy and thus better forecasting effects than the traditional GM (1,1) model, despite their ratios of mean square deviations not differing greatly (i.e., none of them are greater than 0.35). According to Table 2, the prediction accuracy of both improved GM (1,1) models based on new information priority belongs to the first level (excellent), which also demonstrates the necessity of introducing the principle of new information priority to grey prediction modeling on China's CBEC.

Furthermore, we can also draw contrast curves to compare the actual values with the fitted values generated by each model to help more directly and explicitly capture their hidden, easily overlooked differences in annual fitting accuracy. Details are presented in Fig. 2, which was also drawn with Origin 2018.

The results reported in Fig. 2 verify two experimental conclusions. First, compared with the general time series analysis, grey models originated from grey

Fig. 2 Comparison of actual values with fitted values generated by each model

system theory are more suitable for investigating the dynamic changes and future development trends of an object or a system with rapid development and easily influenced by many irregular, occasional factors, just like CBEC. Second, introduction of the principle of new information priority to the improvement of grey models also makes sense since two improved GM (1,1) models both have more stable forecasting effects from a long-term perspective, meaning that their forecast results for fast-growing new things are usually more convincing and reliable.

Finally, the data of the transaction amount of China's CBEC in 2018 is used for verifying of how the idea of new information priority performs in grey models (see Table 4).

Table 4 Comparison of forecast results of transaction amounts of China's CBEC in 2018 generated by each grey model

Year	A.V	Traditional GM (1,1) model			Based on new information priority					
					Reversed GM (1,1) model			Renewal GM (1,1) model		
		F.R	Δ_k (%)	p (%)	F.R	Δ_k (%)	p (%)	F.R	Δ_k (%)	p (%)
2018	9.10	10.31	13.32	86.68	10.14	11.39	88.61	10.18	11.92	88.08

¹ A.V. refers to the actual value (RMB/trillion); F.R. refers to the forecast result (RMB/trillion)

As shown in Table 4, the forecast result for 2018 generated by three grey models are respectively RMB 10.31 trillion, RMB 10.14 trillion and RMB 10.18 trillion, which are all more than its actual value of RMB 9.1 trillion. This sends a vital signal that the development speed of China's CBEC has been slightly slowed down owing to some complex, vague factors which are difficult to clearly quantify, such as the effects brought by the outbreak of the China-US trade war in March, 2018. However, it is still obvious that the idea of new information priority can strengthen the ability of grey models to process this kind of unexpected, occasional events.

4.4 Forecast results

Since the superiority of forecasting effects of two improved GM (1,1) models based on new information priority has been recognized, the next step is to put them into the prediction on the future development of China's CBEC. After a new round of modeling during which the actual value for 2018 is also added to the original sequence, it is found that the renewal GM (1,1) model has a larger mean relative fitting accuracy at 93.51% than that of the reversed GM (1,1) model at 90.50%. Therefore, the renewal GM (1,1) model should be selected to forecast the transaction amounts of China's CBEC from 2019 to 2020. The forecast results are presented in Fig. 3 plotted in Origin 2018.

According to the forecast results, the transaction amounts of China's CBEC from 2019 to 2020 will continue the overall trend of rapid growth, and even promise to end up at RMB 16 trillion after taking the latest data by 2018 into consideration.

Admittedly, since CBEC industry involves different countries, it is born vulnerable to many occasional factors such as domestic policy support, changes in the international situation, trade agreements or even military wars among countries, etc. Therefore, the forecast results generated by the renewal GM (1,1) model in just one or two years can be considered as convincing while long-term predictions are likely to be far from the reality. For example, as we all know, the global outbreak of COVID-19 in 2020 will definitely bring a disastrous blow to various industries especially CBEC, so it's necessary that relevant data in 2020 should be seriously added to the modeling process of the renewal GM (1,1) model with the aim of forecasting the development status of China's CBEC in 2021 or 2022. Indeed, this happens to reflect how the principle of new information priority counts in modeling.

Fig. 3 The forecasted transaction amounts of China's CBEC from 2019 to 2020

5 Conclusions

5.1 Discussion

China's CBEC has developed rapidly since 2008. Since CBEC is sensitive to external changes, its development in China has been largely affected by some policies or trade events, etc. For example, the BRI has provided many new opportunities to China's CBEC industry while the China-US trade war and the increasing of domestic labor costs may continue to hinder the development prospects in the next few years. Moreover, the widespread of the COVID-19 in 2020 has casted a shadow over its rapid development speed. In reality, it's quite difficult to measure and compare the effects caused by these complex realities respectively with accurate data indicators. From the perspective of grey system theory, all these incalculable effects, whether bad or good, are referred as unknown information within the whole CBEC system.

After considering the timely responses of CBEC to external changes due to its nature of sensitivity, the principle of new information priority was introduced to the improvement of grey prediction modeling for CBEC. Thus, this study proposed the improved GM (1,1) models based on new information priority to make CBEC predictions, taking China as a typical example. The experimental results of two time series analysis models were also added to the comparison, leading to two main findings. First, for newly emerging industries that are not mature and do not have large quantities of data for research like CBEC, grey system theory is a feasible forecasting method. Second, whether for time series analysis models or grey models, the improvement idea of new information priority does work in forecasting the development prospects of those industries which are easily influenced by sudden events or external changes. Generally, improved GM (1,1) models based on the principle of new information priority could help to fully exploit known information within the

CBEC system based on available data and to obtain better forecasting effects. In the end, the forecast results generated by the renewal GM (1,1) model, which has been confirmed to have the best prediction accuracy, imply that in 2019 and 2020, China's CBEC will continue to maintain a strong momentum of development since 2008.

5.2 Implications

This study has both theoretical and practical implications. From a theoretical perspective, this study illustrates the applicability of grey models on investigating the dynamic changing rules of newly emerging systems featured with rapid development, a late start and insufficient data like CBEC and it also proves the improvement of forecasting effects brought by the principle of new information priority. Within the research field of CBEC, this study proposes a useful forecasting tool on an initial exploration of its overall development, which can lay a foundation for future research that aims to conduct forecasting in CBEC.

From a practical perspective, research in CBEC is vital and necessary because of its increasing important role it plays in international trade activities. Unlike most existing literature, this study puts the research focus on the overall dynamic changes and development trends of CBEC. Indeed, the experimental results can provide a reference for the implementation and timely adjustments of specific CBEC policies or countermeasures related to laws, logistics and credit to practitioners and scholars within the CBEC industry. For example, the gaps between the actual value and the forecast results for 2018 generated by three grey models proposed in this study send an important signal that China's CBEC has been affected by more negative factors or unexpected incidents (e.g., the China-US trade war erupting in March, 2018), so it depends on relevant decision-makers whether to adjust the development goal or to take certain actions to reverse the adverse situation in the following years. Finally, it also reflects some important information on the development of international trades via research on China's CBEC.

6 Limitations and future research directions

There are some limitations in this study. First, given that CBEC is impacted by many complex factors but its reality of a lack of data cannot afford a complete and fully quantifiable indicator system for predictions, the data of total transaction amounts of China's CBEC is used for an overall prediction based on an exploration of its annual changing rules. However, if a system of specific influencing factors was well set up, the development status of China's CBEC could have been explored from both vertical and horizontal perspectives of development. Indeed, this remains a research gap within the research field of CBEC and creating a complete, systematic and quantifiable indicator system of CBEC based on real data is exactly an important research direction in enriching the contents of this study in the future.

Second, short-term predictions are feasible due to the essence of new information priority. According to the principle of new information priority, the gap between

the reality and the forecast result for 2018 reveals that the development of China's CBEC in 2018 has been more or less adversely affected, which could further help to adjust the forecast results for 2019, and even 2020. However, without taking significantly negative influence caused by well-known events—the COVID-19 in 2020 into consideration, these two well-established models based on new information priority will achieve poor forecasting effects when forecasting China's CBEC in 2021 or even later. Indeed, this remains a common problem among models improved by the principle of new information priority and attemption to make long-term predictions will become another important research direction.

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Compliance with ethical standards

Conflict of interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

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