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RESEARCH ARTICLE

Forecasting the carbon dioxide emissions in 53 countries and regions using a non-equigap grey model

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Abstract
Non-equigap GM(1,1) model with conformable fractional accumulation (CFNGM(1,1)) is proposed to analyze the relationship between energy consumption and carbon dioxide emissions. Two cases are used to prove the validity of the model. In this article, energy consumption is used as input and carbon dioxide emissions are used as output. Carbon dioxide emissions of 53 countries and regions in North America, South America, Europe, Commonwealth of Independent States (CIS), Middle East, Africa, and Asia Pacific are predicted. The forecast results show that the carbon dioxide emissions of 30 countries and regions have risen to varying degrees. The top three countries with carbon dioxide emissions in the next three years are China, the USA, and India. More attention should be paid to the carbon dioxide emissions of China.

Keywords Energy consumption · Carbon dioxide emissions · Conformable fractional accumulation operator · Non-equigap grey model

Introduction

Carbon dioxide is the main greenhouse gas that causes global warming, and the burning of fossil fuels such as coal and petroleum will cause a large amount of carbon dioxide emissions. In the latest research, a large number of scholars have studied various energy issues, such as the industrial solar energy (Wang et al. 2020), clean energy (Wang 2015), coal (Shou et al. 2020), renewable and hydro energy (Utkucan Sahin 2020), and natural gas (Wang and Li 2020).

Energy consumption and carbon dioxide emissions are closely related, so scholars will pay attention to energy and carbon emissions at the same time. Pao et al. (2012) not only studied energy consumption, they also predicted carbon dioxide emissions and economic growth. There are also some scholars specializing in the study of carbon dioxide emissions in certain regions, such as the carbon dioxide emissions of the BRICS and OECD countries (Wu et al. 2020; Saidi and Omri 2020). The above scholars have done a lot of research, but there are some shortcomings. They both studied energy consumption and carbon dioxide emissions separately, and failed to establish a connection between them. The model in this paper makes up for this deficiency.

Carbon dioxide emissions are affected by many factors. Therefore, scholars have studied carbon dioxide emissions from different perspectives. For example, Lin and Agyeman (2020) used energy-related carbon dioxide emission dynamics to assess low-carbon development in sub-Saharan Africa. Tobelmann and Wendler (2020) study the impact of environmental innovation on carbon dioxide emissions. Li et al. (2019) used panel data to analyze the impact of modernization on carbon dioxide emissions. There are also studies on carbon dioxide emissions from the perspectives of urbanization (Zhou et al. 2019) and power generation (Eberle and Heath 2020). From the energy point of view, this paper establishes the connection between energy consumption and carbon dioxide emissions through the non-equigap GM(1,1) model, and analyzes the impact of energy changes on carbon dioxide emissions.

This paper is divided into 6 parts. The literature review in the "Literature review" section is studied from the perspective of grey accumulator operator and non-equigap grey model. The "Non-equigap GM(1,1) model with conformable fractional accumulation" section establishes a non-equigap

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GM(1,1) model with conformable fractional accumulation. The "Validity verification" section uses two cases to verify the rationality of the novel proposed model. The "Analyze the relationship between energy consumption and carbon dioxide emissions" section analyzes the relationship between energy consumption and carbon dioxide emissions in 53 countries and regions. The "Conclusion" section is a summary of the full text.

Literature review

The difference between the grey model and other models is that the grey model contains an accumulation operator. Since Professor Deng Julong proposed a grey model with first-order accumulation, many types of accumulation methods have emerged. For example, the fractional accumulation operator proposed by Wu et al. (2013), the conformable accumulation operator proposed by Ma et al. (2020), adjacent accumulation (Zhao and Wu 2020), and priority accumulation of new information (Wu and Zhang 2018). Many scholars have done a lot of research on this basis. For example, Liu and Yu (2017) established a non-equigap and non-homogeneous grey model from the fractional perspective. Continuous grey model with conformable fractional derivative is proposed by Xie et al. (2020). Xi et al. (2019) studied the NGM(1,1) model from the perspective of new information priority.

In 1993, the non-equigap GM(1,1) model (NGM(1,1)) was proposed by Shi (1993). Later, Professor Deng, the founder of the grey system theory, also conducted a series of studies on the NGM(1,1) model (Deng 1994; Deng 1997). The stability of non-equigap grey control model is studied by Xiao and Li (2009). On this basis, a series of new grey models was derived from non-equigap angles. For example, Wang et al. (2012) proposed the NGM(1,1) power model, which has a very flexible form. Both the NGM(1,1) model and the grey Verhulst model are special forms of the NGM(1,1) power model. Wang and Li (2019) used the non-equigap grey Verhulst model to study the relationship between CO_2 and economic growth. Meanwhile, Li et al. (2020) also studied the non-equigap grey Bernoulli model to analyze the relationship between economic growth and pollutants. The above two latest studies have studied the relationship between the two factors, which inspired the inspiration for this paper. The model in this paper is different from previous time series models, replacing time series with energy consumption. Under other conditions unchanged, analyze the impact of energy consumption on carbon dioxide emissions.

This paper proposes a non-equigap GM(1,1) model with conformable fractional accumulation. The conformable fractional order accumulation was first proposed by Ma et al. (2020). This new type of fractional order is easier to calculate and has a better fitting effect. Some scholars have studied the non-equigap grey model from the perspective of cumulative generation. At present, no scholar has introduced this new type of accumulation operator into the NGM(1,1) model, so a non-equigap GM(1,1) model with conformable fractional accumulation has been proposed. This model considers both energy consumption and carbon dioxide emissions. The nonlinear relationship between energy consumption and carbon dioxide emissions can be reflected by this model.

Non-equigap GM(1,1) model with conformable fractional accumulation

There is an original sequence $X^{(0)}(t_k) = (x^{(0)}(t_1), x^{(0)}(t_2), \cdots, x^{(0)}(t_n))$. If the gap is $\Delta t_k = t_k - t_{k-1} \neq c$, $k = 2, 3, \cdots, n$, c is a constant, and $X^{(0)}(t_k)$ is called a non-equigap sequence. $X^{(r)}(t_k)$ is the r order cumulative sequence of $X^{(0)}(t_k)$:

$X^{(r)}(t_k) = (x^{(r)}(t_1), x^{(r)}(t_2), \cdots, x^{(r)}(t_n))$

where:

$$x^{(r)}(t_k) = \begin{cases} x^{(0)}(t_1) & k = 1 \\ \sum\limits_{j=2}^{k} \dfrac{x^{(0)}(t_j) \times \Delta t_j}{t_j^{\,1-r}} & k = 2, 3, \cdots, n \end{cases}$$

the range of r is (0, 1].

The contiguous mean generation sequence of the non-equigap sequence $X^{(r)}(t_k)$ is $Z^{(r)} = (z^{(r)}(2), z^{(r)}(3), \cdots, z^{(r)}(n))$:

where:

$$z^{(r)}(t_k) = \frac{1}{2}\left(x^{(r)}(t_k) + x^{(r)}(t_{k-1})\right) \tag{1}$$

$$x^{(0)}(t_k) + az^{(r)}(t_k) = b \tag{2}$$

is called the mean value form of CFNGM(1,1). Its whitening differential equation is:

$$\frac{\mathrm{d}x^{(r)}}{\mathrm{d}t} + ax^{(r)} = b \tag{3}$$

a is called the development coefficient and b is called grey action. The least square estimation of CFNGM(1,1) model satisfies:

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B\right)^{-1} B^T Y \tag{4}$$

where:

$$B = \begin{bmatrix} -z^{(r)}(t_2) & 1 \\ -z^{(r)}(t_3) & 1 \\ \vdots & \vdots \\ -z^{(r)}(t_n) & 1 \end{bmatrix}, \quad Y = \begin{bmatrix} \dfrac{x^{(r)}(t_2) - x^{(r)}(t_1)}{t_2 - t_1} \\ \dfrac{x^{(r)}(t_3) - x^{(r)}(t_2)}{t_3 - t_2} \\ \vdots \\ \dfrac{x^{(r)}(t_n) - x^{(r)}(t_{n-1})}{t_n - t_{n-1}} \end{bmatrix} \tag{5}$$

The initial condition of the differential equation in Eq. (3) is:

$$x^{(r)}(1) = x^{(0)}(1)$$

The time response equation can be obtained as:

$$\widehat{x}^{(r)}(t_k) = \left(x^{(0)}(t_1) - \frac{\widehat{b}}{\widehat{a}}\right)e^{-\widehat{a}(t_k - t_1)} + \frac{\widehat{b}}{\widehat{a}} \tag{6}$$

So, the reduction sequence of $\widehat{x}^{(r)}(k)$ can be obtained as:

$$\widehat{x}^{(0)}(t_k) = \begin{cases} \widehat{x}^{(1)}(t_1) & k = 1 \\ \dfrac{t_k^{1-r}\left(\widehat{x}^{(r)}(t_k) - \widehat{x}^{(r)}(t_{k-1})\right)}{\Delta t_k} & k = 2, 3, \cdots, n \end{cases} \tag{7}$$

This paper uses MAPE to measure the stability of the model, as shown in Eq. (8).

$$\mathrm{MAPE} = \frac{1}{n}\sum_{k=1}^{n}\frac{|x^{(0)}(k) - \widehat{x}^{(0)}(k)|}{x^{(0)}(k)} \tag{8}$$

Validity verification

Verify the validity of the CFNGM(1,1) model

In this paper, two cases are used to verify the validity of the CFNGM(1,1) model. The model testing process is shown in the "Verify the validity of the CFNGM(1,1) model" section of the paper. In the "Applicability test of CFNGM(1,1) model in developed and developing countries" section, the USA and India are selected as representatives of developed and developing countries to verify the applicability of the model. The test results all show that the model has good predictive performance.

Case 1 The data in reference Wang et al. (2012) were selected to compare the fitting effects of the two models. In this set of data, the order is $r = 0.99$, parameters $a = 0.001028$, and $b = 539.0238$, and the final fitting results are shown in Table 1. It can be seen from Table 1 that the fitting error of the CFNGM(1,1) model is 0.32%, and the fitting error of the non-equigap GM(1,1) power model is 0.94%. Therefore, we say that the CFNGM(1,1) model is better than the non-equigap GM(1,1) power model.

Case 2 The data in reference Xi et al. (2019) were selected for comparison between fitting and prediction effects. In case 2, the conformable fractional order of the CFNGM(1,1) model is $r = 0.955122$, the parameters $a = -0.00058$, $b = 9.199959$, and the fitting and prediction results are shown in Table 2. In Table 2, the fitting error of the CFNGM(1,1) model is 0.8448%, and the prediction error is 1.7219%. The fitting effect and prediction effect of CFNGM(1,1) model are better than reference Xi et al. (2019). It can be concluded from these two cases that the model proposed in this paper is reasonable and effective.

Table 1 Compare the fitting results of different models in case 1

t_k	$x^{(0)}(t_k)$	Ref (Wang et al. 2012)	CFNGM(1, 1)
100	560	560	560
130	557.54	562.12	556.68
170	536.1	536.10	538.47
210	516.1	511.34	517.88
240	505.6	493.33	500.23
270	486.1	480.29	485.62
310	467.4	467.40	469.12
340	453.8	456.50	452.95
380	436.4	447.43	437.45
MAPE		0.94%	0.32%

Applicability test of CFNGM(1,1) model in developed and developing countries

The USA and India are selected to verify the applicability of the model. The verification results are shown in Table 3. In this verification process, data from 2011 to 2016 are selected for fitting, and data from 2017 to 2019 are used as predictions. Compare the 2017–2019 forecast results with the actual values to calculate MAPE. The MAPE in Table 3 is far less than 10%, which proves that the model is suitable for forecasting in developed and developing countries.

Take the USA as an example, compare the nonlinear model with the linear model. Figure 1 is a linear model diagram of US carbon dioxide emissions. The horizontal axis is energy consumption, and the vertical axis is carbon dioxide emissions. Figure 1 is a scatter plot made by Excel 2010, which is generated by linear trend fitting. The prediction error of the linear model is 5.51%, which is higher than the prediction error of the nonlinear model.

Analyze the relationship between energy consumption and carbon dioxide emissions

The burning of a large number of fossil fuels such as coal, oil, and natural gas has caused the CO_2 in the atmosphere to rise. Carbon emissions are mainly CO_2 emissions. According to the information reviewed, CO_2 contributes as much as 60% to the greenhouse effect. Therefore, it is necessary to study the

Table 2 Compare the fitting results of different models in case 2

k_i	$x^{(0)}(k_i)$	NEGM$(1, 1, x^{(1)}(k_1))$	NEGM$(1, 1, x^{(1)}(k_n))$	IVWA- NEGM$(1, 1)$	NEGM$(1, 1, \rho)$	CFNGM$(1, 1)$
1	9.28					
25	10.71	10.95	10.94	10.76	10.67	10.71
53	11.31	11.25	11.24	11.06	10.96	11.25
83	11.64	11.59	11.58	11.40	11.30	11.67
116	12	11.98	11.97	11.78	11.67	12.06
147	12.23	12.38	12.37	12.17	12.07	12.42
177	13.05	12.78	12.77	12.57	12.46	12.74
237	13.16	13.39	13.38	13.17	13.06	13.25
MAPE		1.2113%	1.2234%	1.5606%	2.2503%	0.8448%
269	13.61	14.05	14.04	13.81	13.70	13.69
355	13.94	14.94	14.93	14.69	14.57	14.34
MAPE		5.2095%	5.1124%	3.4479%	2.6001%	1.7219%

relationship between energy consumption and carbon dioxide emissions.

The data in the "Analyze the relationship between energy consumption and carbon dioxide emissions" section comes from https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy/downloads.html. Although there are many data on energy and carbon dioxide emissions, we have used a grey model with the characteristics of "small samples and poor information" to solve the relationship between energy consumption and carbon dioxide emissions. The reason for this is that Professor Liu Sifeng, the developer of grey system theory, once said why we still use small samples to solve practical problems in the era of big data. There are four reasons:

(1) Understanding that big data starts with small data,
(2) Data with a certain shape in big data is often small data,
(3) In the long history, data at a certain period of time is usually small data,
(4) The information density of big data is low, and it has obvious characteristics of poor information.

Professor Liu believes that big data is like a sea of sand, and small data is the gold hidden in the sea of sand. Therefore, the grey model was selected to solve the relationship between energy consumption and carbon dioxide emissions.

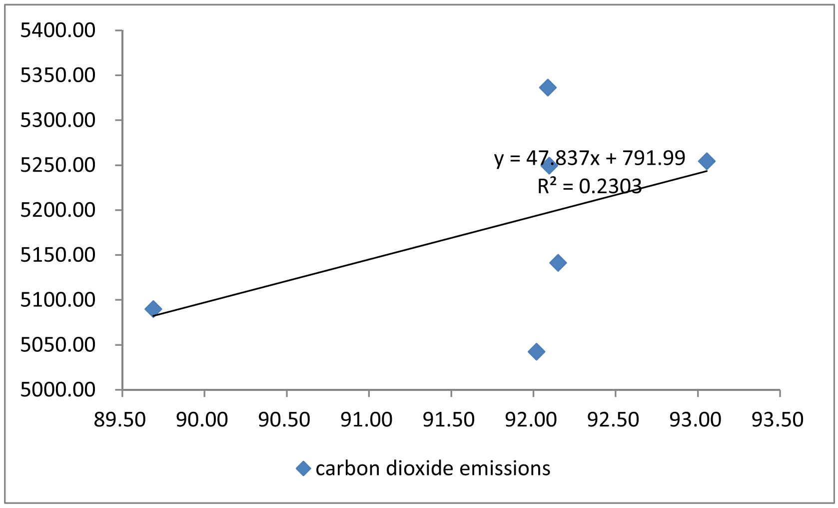
North America

The "North America" section studies the relationship between energy consumption and carbon dioxide emissions in Canada, Mexico, and the USA. Firstly, according to the energy

Table 3 Validation of CFNGM(1,1) model in developed and developing countries

	The USA			India		
	Energy consumption	Carbon dioxide emissions	Forecast	Energy consumption	Carbon dioxide emissions	Forecast
2011	92.09	5336.44	5336.44	23.88	1735.15	1735.15
2012	89.69	5089.97	5089.91	25.11	1848.13	1853.13
2013	92.10	5249.60	5218.32	26.08	1929.35	1930.89
2014	93.05	5254.57	5183.54	27.86	2083.54	2070.94
2015	92.15	5141.41	5135.08	28.77	2149.38	2146.96
2016	92.02	5042.43	5153.98	30.07	2242.89	2251.19
MAPE	-	-	0.71%	-	-	0.24%
2017	92.33	4983.87	5165.80	31.33	2329.82	2354.27
2018	95.60	5116.79	5246.02	33.30	2452.50	2514.09
2019	94.65	4964.69	5138.47	34.06	2480.35	2581.69
MAPE	-	-	3.23%	-	-	2.55%

Fig. 1 Linear model of carbon dioxide emissions



consumption and carbon dioxide emissions data from 2014 to 2019, the parameters a and b in the CFNGM(1,1) model are calculated to obtain the fitted sequence of carbon dioxide emissions. Secondly, according to the 2019 energy consumption growth rate announced by the BP World Energy Statistics Yearbook, assuming that energy consumption will continue to grow at this rate in the next three years, the energy consumption from 2020 to 2022 is calculated. Finally, on the basis of substituting parameters a and b into Eq. (6) to obtain the time response equation, the energy consumption data from 2020 to 2022 can be input into the time response equation to obtain the $x^{(r)}$ series. By using Eq. (7), carbon dioxide emissions for 2020-2022 can be calculated. Take Canada as an example to elaborate on the process.

Energy consumption is used as the independent variable, and carbon dioxide emissions as the dependent variable. There is an energy consumption sequence $t_k = (14.03, 13.99, 13.94, 14.11, 14.35, 14.21)$, and an initial sequence of carbon dioxide emissions $X^{(0)}(t_k) = (553.46, 546.23, 537.78, 549.11, 565.64, 556.19)$.

Step 1. The Δt is calculated.

$$\Delta t = (-0.04, -0.05, 0.17, 0.24, -0.14)$$

Step 2. Particle swarm optimization algorithm is used to find the optimal fractional order $r = 0.000001$, so the cumulative sequence can be obtained.

$$x^{(0.000001)} = (553.46, 551.90, 549.97, 556.59, 566.05, 560.57)$$

Step 3. The contiguous mean generation sequence of the non-equigap sequence $X^{(0.000001)}(t_k)$ can be obtained as:

$$Z^{(0.000001)} = (552.68, 550.93, 553.28, 561.32, 563.31).$$

Step 4. The expression of B and Y is:

$$B = \begin{bmatrix} -552.68 & 1 \\ -550.93 & 1 \\ -553.28 & 1 \\ -561.32 & 1 \\ -563.31 & 1 \end{bmatrix}, Y = \begin{bmatrix} 39.04 \\ 38.58 \\ 38.92 \\ 39.42 \\ 39.14 \end{bmatrix}.$$

The parameters $\widehat{a}$ and $\widehat{b}$ are calculated according to the least squares method.

$$\widehat{a} = -0.04339, \widehat{b} = 14.88381$$

Step 5. The parameters $\widehat{a} = -0.04339, \widehat{b} = 14.88381$ are brought into Eq. (6):

$$\widehat{x}^{(0.000001)} = (553.46, 551.91, 549.97, 556.58, 565.99, 560.49).$$

Step 6. The restored sequence of the fitted value is:

$$\widehat{x}^{(0)} = (553.46, 543.68, 540.68, 548.71, 563.03, 558.74).$$

Step 7. The growth rate of energy consumption in 2018–2019 is − 0.9%. According to this growth rate, the energy consumption in 2020–2022 is calculated as $t_7 = 14.09$, $t_8 = 13.96$, $t_9 = 13.83$.

Step 8. The 2020–2020 energy consumption values 14.09, 13.96, and 13.83 are introduced into Eq. (6), and the time response sequence for the next 3 years can be obtained as:

$$\widehat{x}^{(0.000001)}(t_7) = 555.80, \widehat{x}^{(0.000001)}(t_8) = 550.74, \widehat{x}^{(0.000001)}(t_9) = 545.71$$

Step 9. The reduction sequence of the predicted value of carbon dioxide emissions from 2020 to 2022 is:

$$\widehat{x}^{(0)}(t_7) = 550.91, \widehat{x}^{(0)}(t_8) = 542.87, \widehat{x}^{(0)}(t_9) = 534.79$$

The detailed calculation process of the CFNGM(1,1) model is given above by taking Canadian energy consumption and carbon dioxide emissions as examples. Table 4 shows the carbon dioxide emissions of Mexico and the USA. The fitting errors of Mexico and the USA are 0.61% and 0.75%, respectively. The fitting accuracy shows that the model is suitable for carbon dioxide emission prediction.

Judging from the forecast results of the three countries in North America, Canada and Mexico have shown a downward trend in carbon dioxide emissions as energy consumption decreases. With the reduction of energy consumption in the USA, its carbon dioxide emissions have shown an upward trend. The USA shut down a large number of coal power plants, which should be one of the reasons for the reduction in energy consumption in the USA. Although the US coal use has fallen sharply, it is not enough to offset the rise in emissions from other economic sectors. Those neglected industrial plants and factories have also become a greater source of climate pollution. One of the reasons for the increase in carbon dioxide emissions in the USA may also be related to the weather. A relatively cold winter has led to a substantial increase in the demand for oil and natural gas heating in areas such as New England. Therefore, the USA is likely to see an increase in carbon dioxide emissions in the face of reduced energy consumption, so it should pay attention to this problem.

South America

The carbon dioxide emissions of four South American countries, including Argentina, Brazil, Colombia, and Venezuela, are predicted in the "South America" section. The prediction results are shown in Table 5. The energy consumption of each country from 2020 to 2022 is calculated based on the growth rate of energy consumption from 2018 to 2019. It can be seen from Table 5 that the carbon dioxide emissions of Argentina and Venezuela will be decreasing in the next 3 years. The carbon dioxide emissions of Brazil and Colombia will increase in the next 3 years. As energy consumption increases (decreases), carbon dioxide emissions show a corresponding increase (decrease) trend, but there is a nonlinear relationship between energy consumption and carbon dioxide emissions.

Europe

In the "Europe" section, the carbon dioxide emissions of 14 European countries are predicted, and the predicted results are shown in Table 8. Table 6 and Table 7 are the original data of energy consumption and carbon dioxide emissions, respectively. Table 6 lists the growth rate of energy consumption in 2018–2019. Assuming that the next 3 years will continue to develop at this growth rate, the energy consumption for the next 3 years is calculated, as shown in Table 6.

The energy consumption in Table 6 is used as the independent variable, and the carbon dioxide data in Table 7 is used as the dependent variable to predict the carbon dioxide emissions of 14 European countries. In Table 8, Germany's carbon

Table 4 Forecasting carbon dioxide emissions in Mexico and the USA. Energy consumption: Exajoules

	Mexico			The USA		
	Energy consumption	Carbon dioxide emissions	Forecast	Energy consumption	Carbon dioxide emissions	Forecast
2014	7.70	459.63	459.63	93.05	5254.57	5254.57
2015	7.69	463.12	461.37	92.15	5141.41	5025.50
2016	7.79	468.79	466.84	92.02	5042.43	5054.99
2017	7.90	476.95	472.18	92.33	4983.87	5065.57
2018	7.83	466.58	467.76	95.60	5116.79	5114.40
2019	7.72	454.97	462.23	94.65	4964.69	4981.02
MAPE	-	-	0.61%	-	-	0.75%
2020	7.61	-	456.91	93.70	-	4997.63
2021	7.51	-	452.10	92.77	-	5014.15
2022	7.40	-	446.66	91.84	-	5029.51

Table 5 Forecasting carbon dioxide emissions in Argentina, Brazil, Colombia, and Venezuela. Exajoules, million tonnes

	Energy consumption	Carbon dioxide emissions	Forecast	Energy consumption	Carbon dioxide emissions	Forecast
	Argentina			Brazil		
2014	3.51	182.75	182.75	12.40	503.78	503.78
2015	3.59	186.02	183.92	12.23	487.04	466.35
2016	3.58	185.76	185.00	11.92	450.37	451.48
2017	3.57	182.81	184.03	12.06	457.23	446.30
2018	3.54	180.39	181.58	12.13	442.25	452.68
2019	3.46	174.88	175.08	12.40	441.30	463.23
MAPE	-	-	0.50%	-	-	2.37%
2020	3.39	-	168.39	12.68	-	480.78
2021	3.31	-	161.40	12.96	-	499.33
2022	3.24	-	155.08	13.24	-	518.60
	Colombia				Venezuela	
2014	1.70	89.16	89.16	3.41	171.06	171.06
2015	1.71	89.76	89.19	3.29	164.39	167.20
2016	1.81	95.14	93.18	2.99	151.39	150.71
2017	1.84	89.36	93.27	2.86	142.73	138.41
2018	1.85	90.02	93.34	2.45	119.57	119.57
2019	1.92	100.63	95.95	2.23	102.39	104.30
MAPE	-	-	2.57%	-	-	1.18%
2020	2.00	-	98.19	2.02	-	93.71
2021	2.08	-	100.20	1.83	-	84.59
2022	2.16	-	102.10	1.66	-	76.87

dioxide emissions fitting error is the largest at 2.07%, which is far below 10%. Therefore, it shows that the model is suitable for carbon dioxide emission prediction in European countries.

The carbon dioxide emission prediction results of these 14 European countries show that carbon dioxide emissions of Austria, Belgium, and Turkey will show an increasing as energy consumption increase. The carbon dioxide emissions of Finland, Germany, Italy, Poland, Spain, Ukraine, and the UK in the next 3 years will show a decreasing trend as energy consumption decreases. Greece's carbon dioxide emissions have fluctuated up and down. Its carbon emissions are relatively stable.

France, Norway, and Sweden are quite special. The forecast of France and Norway shows that as energy consumption decreases, carbon dioxide emissions have increased. In April 2020, the French government launched the Energy Transition Action Schedule 2019–2028 "Multi-Year Energy Plan." It plans to shut down 14 nuclear reactors by 2035 and reduce

Table 6 The original data of energy consumption. Exajoules

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Norway	Poland	Spain	Sweden	Turkey	Ukraine	UK
2014	1.38	2.40	1.16	9.87	13.17	1.12	6.23	1.87	3.93	5.54	2.11	5.23	4.29	8.02
2015	1.39	2.44	1.15	9.92	13.40	1.13	6.37	1.89	3.98	5.61	2.18	5.72	3.55	8.11
2016	1.43	2.63	1.18	9.76	13.62	1.11	6.43	1.91	4.15	5.66	2.14	6.01	3.72	8.01
2017	1.47	2.66	1.14	9.70	13.78	1.17	6.49	1.92	4.32	5.74	2.21	6.37	3.46	7.99
2018	1.44	2.59	1.15	9.87	13.44	1.16	6.53	1.90	4.38	5.82	2.17	6.29	3.54	7.96
2019	1.50	2.71	1.10	9.68	13.14	1.15	6.37	1.77	4.28	5.72	2.24	6.49	3.41	7.84
Growth rate	4.3%	4.8%	− 4.3%	− 1.9%	− 2.2%	− 1.3%	− 2.4%	− 7.2%	− 2.4%	− 1.7%	3.5%	3.2%	− 3.9%	− 1.6%
2020	1.56	2.84	1.05	9.50	12.85	1.13	6.22	1.64	4.17	5.62	2.32	6.70	3.27	7.71
2021	1.63	2.98	1.01	9.31	12.57	1.12	6.07	1.52	4.07	5.53	2.40	6.91	3.14	7.59
2022	1.70	3.12	0.96	9.14	12.29	1.10	5.93	1.41	3.98	5.43	2.49	7.13	3.02	7.47

Table 7 The original data of carbon dioxide emissions. Million tonnes

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Norway	Poland	Spain	Sweden	Turkey	Ukraine	UK
2014	58.94	111.73	48.06	301.30	751.08	77.84	317.72	35.39	293.34	273.58	46.07	335.13	244.78	458.08
2015	60.95	118.28	45.15	306.66	755.63	75.22	329.75	35.50	293.33	289.25	46.46	340.57	192.31	439.73
2016	61.85	120.12	48.58	312.10	770.46	72.04	329.95	34.28	306.04	282.23	46.60	358.99	213.23	415.79
2017	64.67	122.11	45.49	318.11	760.95	76.59	333.43	34.11	315.49	299.79	45.83	397.11	185.81	404.12
2018	62.83	125.07	46.79	307.20	731.32	74.35	332.08	34.79	319.53	293.63	45.04	392.07	193.12	396.89
2019	64.69	124.48	42.98	299.24	683.77	71.70	325.36	33.58	303.89	278.51	46.34	383.26	185.44	387.09

Table 8 Forecast results of 14 European countries. Million tonnes

	Austria	Belgium	Finland	France	Germany	Greece	Italy	Norway	Poland	Spain	Sweden	Turkey	Ukraine	UK
2014	58.94	111.73	48.06	301.30	751.08	77.84	317.72	35.39	293.34	273.58	46.07	335.13	244.78	458.08
2015	60.78	118.01	46.18	306.13	730.93	74.12	329.74	34.88	294.37	288.34	46.46	341.67	194.32	427.65
2016	62.34	120.98	47.79	307.63	748.50	73.12	330.31	34.74	304.82	288.48	46.14	363.01	203.96	421.35
2017	63.94	123.87	45.98	310.67	762.08	75.77	331.87	34.55	313.92	289.92	46.11	381.87	189.75	408.06
2018	62.83	123.34	45.78	309.16	741.06	73.53	332.65	34.31	315.98	290.69	45.79	390.24	194.24	401.58
2019	65.11	124.01	43.05	309.42	716.87	73.52	325.99	33.75	309.16	286.10	45.75	393.92	187.13	381.29
MAPE	0.48%	0.69%	1.21%	1.33%	2.07%	1.28%	0.16%	1.05%	0.68%	1.59%	0.75%	1.42%	1.50%	1.39%
2020	67.51	127.39	39.36	314.58	694.22	73.17	322.10	34.35	303.21	285.05	44.89	406.70	179.59	352.67
2021	70.29	131.14	36.43	319.81	672.70	73.46	317.95	34.84	297.91	284.23	43.97	420.22	172.58	326.52
2022	73.08	135.16	33.31	324.99	651.64	73.08	314.08	35.12	293.07	282.82	43.01	434.53	166.10	302.98

the proportion of nuclear power in France's total electricity generation to 50%. The installed capacity of renewable energy power generation is expected to be significantly higher than the current level, with the new installations mainly coming

Table 9 The original data of energy consumption and carbon dioxide emissions in CIS. Exajoules, million tonnes

	Azerbaijan	Belarus	Kazakhstan	Russian Federation	Turkmenistan	Uzbekistan
Energy consumption						
2014	0.56	1.07	2.70	28.71	1.00	1.99
2015	0.62	0.97	2.66	28.14	1.20	1.89
2016	0.61	0.96	2.70	28.76	1.19	1.78
2017	0.60	0.98	2.86	28.87	1.17	1.79
2018	0.62	1.05	3.15	30.04	1.31	1.83
2019	0.66	1.06	3.10	29.81	1.45	1.78
Growth rate	6.6%	0.9%	− 1.7%	− 0.8%	10.1%	− 2.5%
2020	0.70	1.07	3.05	29.57	1.59	1.74
2021	0.75	1.08	3.00	29.33	1.75	1.70
2022	0.79	1.09	2.94	29.10	1.93	1.65
Carbon dioxide emissions						
2014	31.04	57.12	212.49	1530.76	60.46	109.63
2015	33.62	52.96	207.51	1490.97	71.54	104.14
2016	33.14	53.34	208.49	1504.80	70.86	97.30
2017	32.12	54.44	219.40	1486.85	70.16	97.51
2018	32.78	58.40	243.82	1548.41	78.15	101.78
2019	34.89	59.02	239.89	1532.56	85.78	98.49

Table 10 Forecast results of carbon dioxide emissions of the CIS. Million tonnes

	Azerbaijan	Belarus	Kazakhstan	Russian Federation	Turkmenistan	Uzbekistan
2014	31.04	57.12	212.49	1530.76	60.46	109.63
2015	33.52	53.72	205.97	1478.71	71.54	104.18
2016	32.63	53.23	208.94	1504.80	71.18	97.97
2017	32.23	54.34	221.10	1504.72	70.05	98.45
2018	33.24	58.16	243.26	1545.50	77.87	100.68
2019	34.93	58.66	239.89	1529.65	85.84	97.92
MAPE	0.61%	0.47%	0.33%	0.40%	0.18%	0.56%
2020	36.42	59.20	236.03	1522.73	93.82	95.66
2021	38.28	59.74	232.17	1515.82	102.92	93.41
2022	39.56	60.28	227.55	1509.22	113.18	90.60

from wind, electricity and solar energy. And the French government has also introduced a series of incentive policies to promote this plan. However, affected by the COVID-19, many of the previously announced renewable energy projects in France have not yet been released and tendered, and existing projects have also been delayed to varying degrees. Therefore, there may be an increase in carbon dioxide emissions in France. In order to reduce carbon emissions, starting

Table 11 Forecast results of carbon dioxide emissions in the Middle East. Exajoules, million tonnes

	Iran	Israel	Kuwait	Qatar	Saudi Arabia	United Arab Emirates
Energy consumption						
2014	10.28	0.97	1.49	1.84	10.50	4.08
2015	10.22	1.02	1.62	2.05	10.83	4.48
2016	10.79	1.04	1.69	2.00	10.98	4.66
2017	11.30	1.08	1.58	1.92	11.01	4.72
2018	11.83	1.09	1.57	1.99	10.91	4.80
2019	12.34	1.13	1.64	2.02	11.04	4.83
Growth rate	4.3%	3.7%	4.2%	1.6%	1.2%	0.6%
2020	12.88	1.17	1.71	2.06	11.16	4.86
2021	13.44	1.21	1.78	2.09	11.29	4.89
2022	14.02	1.25	1.85	2.12	11.43	4.92
Carbon dioxide emissions						
2014	578.20	66.73	90.39	92.17	570.95	245.13
2015	570.16	69.79	98.53	104.00	588.43	267.06
2016	596.63	69.12	102.91	101.53	599.54	276.90
2017	612.64	70.99	94.71	97.03	592.99	280.74
2018	644.14	70.69	94.30	100.17	573.75	284.97
2019	670.71	73.08	97.30	102.49	579.92	282.58
Forecast results						
2014	578.20	66.73	90.39	92.17	570.95	245.13
2015	570.16	69.39	97.56	103.57	590.14	267.43
2016	593.14	69.54	101.74	101.51	588.16	276.64
2017	618.16	71.16	95.12	97.09	586.00	280.48
2018	643.79	70.94	94.54	100.60	582.13	282.93
2019	668.98	72.64	98.75	102.41	588.44	284.74
MAPE	0.30%	0.40%	0.72%	0.17%	1.05%	0.30%
2020	695.51	73.74	102.94	104.65	589.56	285.78
2021	723.40	74.78	107.13	106.39	591.14	286.83
2022	752.62	75.74	111.32	108.10	592.74	287.88

Table 12 Forecast results of carbon dioxide emissions in the Africa. Exajoules, million tonnes

	Egypt	South Africa	Eastern Africa	Western Africa
Energy consumption				
2014	3.47	5.22	1.98	1.87
2015	3.55	5.05	2.05	2.15
2016	3.74	5.30	2.04	2.20
2017	3.84	5.25	2.15	2.39
2018	3.92	5.30	2.26	2.52
2019	3.89	5.40	2.35	2.60
Growth rate	− 0.8%	2.0%	4.3%	3.0%
2020	3.86	5.51	2.45	2.67
2021	3.82	5.62	2.56	2.75
2022	3.79	5.73	2.67	2.84
Carbon dioxide emissions				
2014	203.51	469.11	99.34	109.03
2015	207.59	451.71	103.01	125.33
2016	216.74	470.51	103.23	130.26
2017	218.83	465.81	110.83	141.66
2018	221.26	470.38	116.43	148.92
2019	217.44	478.82	116.63	153.69
Forecast results				
2014	203.51	469.11	99.34	109.03
2015	208.14	451.37	104.35	125.81
2016	216.09	470.51	103.74	130.26
2017	218.39	466.70	109.16	140.61
2018	220.77	470.51	114.34	148.93
2019	218.49	478.14	118.52	154.24
MAPE	0.25%	0.07%	1.12%	0.25%
2020	217.51	486.51	123.18	158.67
2021	216.08	494.85	128.28	163.60
2022	215.20	503.17	133.33	169.20

from January 2020, Norwegian aviation fuel suppliers are required to add 0.5% biofuel to all aviation fuel. However, there are not many suppliers of this fuel. The demand for biofuels is strong, but the output is not enough. This way of reducing emissions has certain limitations. In Sweden, carbon dioxide decreases as energy consumption increases. This phenomenon in Sweden is in line with the facts. The energy consumption in this article refers to the consumption of primary energy. In addition to non-renewable energy such as coal and oil, primary energy also includes renewable energy such as solar energy, water power, and wind power. As early as 2012, hydropower in Sweden accounted for 48% of the total power generation, and wind power accounted for 4.4% of the total power generation. Hydropower and wind power have shown an upward trend, while fossil energy power generation has fallen by 8%. Therefore, although energy consumption is increasing in Sweden, its carbon dioxide may appear to decrease.

Table 13 The original data of energy consumption in the Asia Pacific. Exajoules

Energy consumption	Australia	Bangladesh	China	China Hong Kong	India	Indonesia	Japan	Malaysia	Pakistan	Philippines	Singapore	South Korea	Sri Lanka	China Taiwan	Thailand	Vietnam
2014	5.75	1.13	124.2	1.14	27.86	7.09	19.24	3.94	2.77	1.45	3.15	11.64	0.23	4.82	5.09	2.61
2015	5.84	1.32	125.38	1.18	28.77	7.1	18.97	4	2.92	1.59	3.35	11.87	0.29	4.77	5.25	2.9
2016	5.88	1.34	126.95	1.21	30.07	7.3	18.65	4.21	3.19	1.73	3.48	12.16	0.31	4.85	5.36	3.11
2017	5.87	1.39	130.83	1.29	31.33	7.57	18.89	4.27	3.37	1.9	3.59	12.37	0.33	4.87	5.45	3.32
2018	6	1.48	135.77	1.3	33.3	8.23	18.84	4.21	3.48	1.96	3.61	12.55	0.35	4.93	5.6	3.72
2019	6.41	1.76	141.7	1.24	34.06	8.91	18.67	4.26	3.56	2.02	3.55	12.37	0.36	4.81	5.61	4.12
Growth rate	6.90%	18.60%	4.40%	− 4.70%	2.30%	8.30%	− 0.9-0%	1.30%	2.40%	3.50%	− 1.50%	− 1.40%	2.80%	− 2.40%	0.30%	10.70%
2020	6.85	2.09	147.89	1.18	34.83	9.65	18.51	4.32	3.65	2.09	3.49	12.19	0.37	4.69	5.63	4.56
2021	7.32	2.47	154.34	1.13	35.63	10.46	18.34	4.37	3.73	2.17	3.44	12.02	0.38	4.58	5.64	5.05
2022	7.83	2.94	161.08	1.08	36.44	11.33	18.18	4.43	3.82	2.24	3.39	11.85	0.39	4.47	5.66	5.59

CIS

In the "CIS" section, the carbon dioxide emissions of six CIS countries are predicted. The original data of energy consumption and carbon dioxide emissions of CIS countries are shown in Table 9, and the growth rate data is also listed in Table 9.

The results of carbon dioxide emission forecasts for CIS countries are shown in Table 10. It can be seen in Table 10 that the fitting error of the six countries does not exceed 1%, indicating that the model is suitable for predicting the carbon dioxide emissions of the CIS. The forecast results show that the carbon dioxide emissions of Azerbaijan, Belarus, and Turkmenistan from 2020 to 2022 are on the rise with the increase in energy consumption. Kazakhstan, Russian Federation, and Uzbekistan show a downward trend in carbon dioxide emissions from 2020 to 2022 as energy consumption decreases.

Middle East

In 2019, the oil reserves in the Middle East accounted for 61.5% of the world's oil reserves, and the oil production in the Middle East accounted for 30.7% of the world's oil production. The Middle East is the region with the largest oil reserves and the most oil production and export in the world. In the "Middle East" section, the carbon dioxide emissions of six countries in the Middle East are predicted. The original data of energy consumption, carbon dioxide emissions, and the final prediction results are included in Table 11. From Table 11, it can be seen that the energy consumption of these six Middle Eastern countries has increased from 2018 to 2019. According to this growth rate, the energy consumption of 2020–2022 will also increase. The forecast results show that as energy consumption increases, carbon dioxide emissions in these six countries are also increasing year by year. Among them, Iran's carbon dioxide emissions rank first among the six countries, followed by Saudi Arabia. Israel has the least carbon dioxide emissions.

Africa

Africa's carbon dioxide emissions forecast results are shown in Table 12. The carbon dioxide emissions forecasts of South Africa, Eastern Africa, and Western Africa increase with the increase in energy consumption, and only Egypt's carbon dioxide emissions show a downward trend. Although Egypt's forecast shows a downward trend, it is still higher than the forecasts of Eastern Africa and Western Africa. South Africa's carbon dioxide emission forecast results rank first among these four regions. The forecast value of South Africa in 2022 is 503.17, which is 3.77 times the forecast value of Eastern Africa in 2022. Therefore, South Africa should take measures to prevent carbon dioxide emissions from continuing to rise.

Asia Pacific

The carbon dioxide emissions of 16 countries and regions in the Asia Pacific region are predicted in the "Asia Pacific" section. The original data of energy consumption in the Asia Pacific region is shown in Table 13. It can be seen from Table 13 that China's energy consumption in the Asia Pacific region is the largest and is still on the rise. In China, energy consumption is inseparable from its population. As we

Table 14 The original data of carbon dioxide emissions in the Asia Pacific. Million tonnes

	2014	2015	2016	2017	2018	2019
Australia	405.73	411.33	411.81	409.64	411.10	428.25
Bangladesh	65.53	79.60	80.42	84.14	90.48	106.50
China	9239.86	9185.99	9137.63	9297.99	9507.11	9825.80
China Hong Kong SAR	89.75	90.53	92.70	98.93	99.50	94.68
India	2083.54	2149.38	2242.89	2329.82	2452.50	2480.35
Indonesia	486.14	497.93	502.00	526.97	580.72	632.09
Japan	1249.31	1209.89	1193.22	1187.49	1164.18	1123.12
Malaysia	242.20	245.75	251.45	241.43	243.47	244.47
Pakistan	152.34	159.91	175.72	189.65	197.69	198.30
Philippines	97.31	106.21	116.44	128.87	133.75	140.10
Singapore	190.94	202.71	217.00	228.93	225.29	218.88
South Korea	614.91	624.17	629.56	645.19	662.19	638.61
Sri Lanka	14.23	17.87	20.25	21.67	21.57	23.41
China Taiwan	275.18	271.66	280.28	288.35	287.00	278.62
Thailand	280.71	291.44	298.21	299.04	306.07	301.68
Vietnam	157.38	183.42	195.47	196.12	237.01	285.86

Table 15 The forecast result of carbon dioxide emissions in the Asia Pacific. Million tonnes

	Australia	Bangladesh	China	China Hong Kong	India	Indonesia	Japan	Malaysia	Pakistan	Philippines	Singapore	South Korea	Sri Lanka	China Taiwan	Thailand	Vietnam
2014	405.73	65.53	9239.86	89.75	2083.54	486.14	1249.31	242.20	152.34	97.31	190.94	614.91	14.23	275.18	280.71	157.38
2015	410.22	79.60	9119.69	90.51	2155.76	492.89	1210.90	246.37	160.13	106.15	204.34	620.77	18.05	273.86	292.98	174.00
2016	410.53	80.99	9184.81	92.74	2241.39	507.58	1163.97	250.09	176.49	116.37	215.15	635.09	20.06	279.29	296.24	192.51
2017	409.63	84.06	9317.07	98.76	2321.20	528.25	1168.43	244.59	188.23	128.87	224.13	645.23	21.16	283.22	299.06	209.64
2018	414.52	89.61	9531.30	99.43	2448.34	578.40	1177.53	241.15	195.56	134.62	226.58	653.97	22.31	288.99	304.67	237.49
2019	427.21	106.89	9801.14	94.89	2488.15	632.64	1158.38	244.34	200.86	139.34	222.45	644.60	23.22	280.29	303.47	279.29
MAPE	0.28%	0.36%	0.32%	0.09%	0.20%	0.48%	1.40%	0.52%	0.61%	0.22%	0.99%	0.60%	1.43%	0.71%	0.37%	2.67%
2020	436.04	127.67	10,109.26	90.42	2535.21	692.66	1133.67	244.15	206.68	144.79	217.62	635.80	23.84	266.89	304.22	331.19
2021	444.19	151.93	10,440.25	86.69	2583.83	759.75	1109.07	243.35	211.97	151.14	213.54	627.50	24.49	254.77	304.44	399.96
2022	451.82	182.39	10,796.55	82.94	2632.52	833.58	1085.31	243.07	217.86	157.00	209.58	619.16	25.15	243.30	305.19	492.86

all know, China is a country with a large population, and the electricity needed by these people needs to consume a lot of energy. However, in recent years, non-fossil energy power supply capacity in China has continued to increase.

The original data of carbon dioxide emissions from Asia Pacific regions from 2014 to 2019 are shown in Table 14. Energy consumption in the Asia Pacific regions ranks first is China, and it also has the highest carbon dioxide emissions. India and Japan's carbon dioxide emissions are closely behind China. Carbon dioxide emissions of China are much higher than those of other countries in the Asia Pacific region. Carbon dioxide is the main greenhouse gas, so the forecast of carbon dioxide emissions can be warned in advance to remind the government whether to adjust the energy structure.

The forecast results of carbon dioxide emissions in the Asia Pacific region are shown in Table 15. The forecast results show that carbon dioxide emissions of 10 countries including Australia, Bangladesh, China, India, Indonesia, Pakistan, Philippines, Sri Lanka, Thailand, and Vietnam will show an upward trend from 2020 to 2022. The results of carbon dioxide emissions forecasts in China show an increase year by year, and will exceed 10 billion tonnes of carbon dioxide, which should be taken seriously. With the reduction of energy consumption in China Hong Kong SAR, Japan, Singapore, South Korea, and China Taiwan, carbon dioxide emissions have shown a downward trend. The forecast results show that as energy consumption increases, there is a trend of decreasing carbon dioxide emissions in Malaysia. Currently, the Ministry of Transport of Malaysia is promoting the development of green logistics to reduce the industry's carbon footprint. The transportation industry is Malaysia's second largest source of carbon emissions. Therefore, the goal of reducing carbon emissions is achieved through green logistics cooperation to improve efficiency.

Conclusion

The non-equigap GM(1,1) model with conformable fractional accumulation is proposed to predict the carbon dioxide emissions of 53 countries and regions around the world. In order to verify the effectiveness of the model in this paper, MAPE is used as a measurement standard, and two cases are compared to illustrate the validity of the model in this paper. The distribution intervals of all fractional orders are counted as shown in Fig. 2. In the context of the application of predicting carbon dioxide emissions, the proportion of conformable fractional orders less than 0.1 is 66.04%, and the conformable fractional orders in the range of 0.1–0.5 account for 15.09%, a total of 81.13%. This also shows that the conformable fractional order has a better prediction effect when the r is smaller.

In this article, energy consumption is used as input, and carbon dioxide emissions are used as output. The relationship

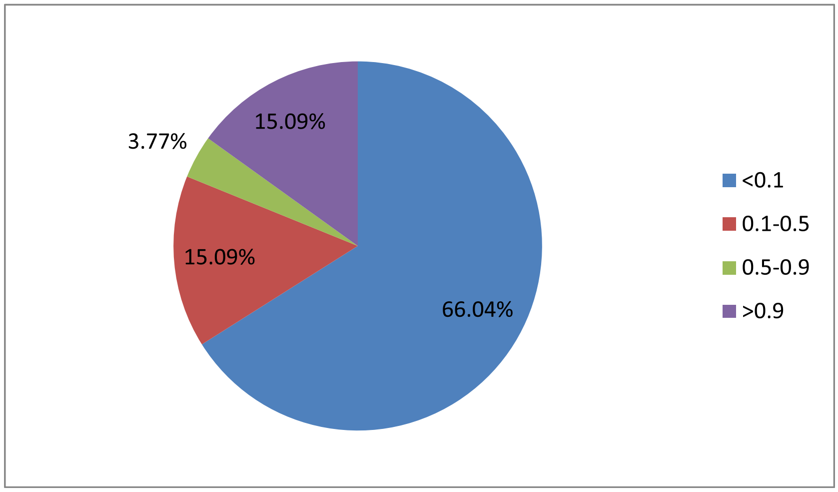


Fig. 2 Interval statistics of the conformable fractional distribution

between energy consumption and carbon dioxide emissions is analyzed. Energy consumption and carbon dioxide emissions show a nonlinear relationship. The carbon dioxide emission forecast is divided into seven parts, including North America, South America, Europe, CIS, Middle East, Africa, and Asia Pacific. In North America, carbon dioxide in the USA is on the rise. The forecast results of carbon dioxide emissions of South American countries Brazil and Colombia from 2020 to 2022 show an upward trend. With the growth of energy consumption, carbon dioxide emissions have also increased in three European countries, including Austria, Belgium, and Turkey. The forecast of France and Norway shows that as energy consumption decreases, carbon dioxide emissions have increased. In CIS, the countries with increasing carbon dioxide emissions are Azerbaijan, Belarus, and Turkmenistan. In the Middle East, countries with increased carbon dioxide emissions include Iran, Israel, Kuwait, Qatar, Saudi Arabia, and United Arab Emirates. In Africa, the forecast results of carbon dioxide emissions in the three regions have increased, including South Africa, Eastern Africa, and Western Africa. In Asia Pacific, countries with rising carbon dioxide emissions include Australia, Bangladesh, China, India, Indonesia, Pakistan, Philippines, Sri Lanka, Thailand, and Vietnam. The above are the countries with increased carbon dioxide emissions forecast results. There are also special circumstances in the prediction results. For example, the prediction results of the USA, France, and Norway show that as energy consumption decreases, carbon dioxide emissions have increased. In Sweden and Malaysia, energy consumption is increasing, but carbon dioxide is decreasing. The emergence of these situations is closely related to the country's carbon dioxide emission policy. Enough attention should be paid to countries that predict increased carbon dioxide emissions.

There may be some uncertain factors in the forecasting process, such as technological changes and government policies. Assuming that certain uncertain factors appear in the historical trend of carbon dioxide that will affect future changes in carbon dioxide emissions, buffer operators can be used to eliminate this effect. And the energy consumption data used in the prediction of future carbon dioxide is calculated based on the latest data. To prevent the interference of uncertain factors, we can only forecast the data for the next year. After the actual data appears in the next year, the model data will be updated again to ensure the accuracy of the forecast. These suggestions are provided for reference when similar problems arise.

Authorship contribution statement Zhicun Xu: data curation, methodology, project administration, resources, validation, visualization, writing-original draft. Lianyi Liu: formal analysis, investigation, software writing-review and editing. Lifeng Wu: conceptualization, funding acquisition, supervision.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval and consent to participate Not applicable

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