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"Gheorghe Asachi" Technical University of Iasi, Romania

A NOVEL OF FRACTIONAL ORDER PREDICTIVE MODEL ON CARBON EMISSION INTENSITY IN CHINA'S TRANSPORTATION SECTOR

Li Cheng *, Xing Jian

College of Air Transportation, Shanghai University of Engineering Science, Shanghai 201620, China

Abstract

The research on the carbon emission of transportation sector has always been concerned. The purpose of this paper is to establish a model to predict whether China's transportation sector can meet the emission reduction commitments under the Paris agreement. We have collected data of carbon dioxide emissions and Gross Domestic Product (GDP) of China's transportation sector for 18 years from 2000 to 2017. By comparing the accuracy of GM(1,1), fractional order GM(1,1), combination model of GM(1,1) and Markov model and the combination model of fractional order GM(1,1) and Markov model, the results showed that the combination model of fractional order GM(1,1) and Markov model had the highest prediction accuracy. Afterwards, we got that the carbon emission intensity of transportation sector from China in 2030 will be 63.70% lower than that in 2005. Under the current emission reduction measures and intensity, China's transportation sector will be able to meet the minimum emission reduction targets promised, but it will be difficult to achieve the maximum emission reduction targets by 2030. In the end, we put forward some policy suggestions to the relevant departments to reduce the carbon emission intensity of transportation sector.

Key words: carbon emission intensity, emission reduction commitment, fractional order grey model, transportation sector

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1. Introduction

Since the last century, global warming has become a problem that human can't ignore with the widespread use of fossil energy (Li et al., 2020a; Zhou et al., 2019). As we all know, global warming has a great impact on the ecological environment and threatens the survival of human beings (Ding et al., 2017; Fang et al., 2018; Miao, 2017; Sun et al., 2017; Wang and Ye, 2017). The Intergovernmental Panel on Climate Change (IPCC) report said that CO_2 emissions was an important reason for the global warming, and that human activities accounted for a large part of CO_2 emissions. As one of the main reasons of global warming, the prediction of carbon emissions attracted a lot of attention (Ding et al., 2017; Sun et al., 2017; Şahin, 2019; Xu et al., 2016). In order to cut down greenhouse gas emissions and slow down global warming, the United Nations adopted the Paris agreement in December 2015. Many countries had set objectives to slow greenhouse effect (Qiao et al., 2020).

With the rapid economic development, China has become the world's largest energy consumer and carbon emitter (Ding et al., 2017). At the same time, China's rapid urbanization has contributed to the increase in carbon emissions (Li et al., 2020b). China urgently needs to change its traditional development model to a healthier and more sustainable one (Zhang and Wei, 2015). Since the 13th five-year plan, China has been vigorously advocating low-carbon development (Xu et al., 2019).

Transportation is a pivotal economic sector that supports social and economic development (Li et al.,

* Author to whom all correspondence should be addressed: e-mail: lcheng8066@126.com

2020c). It promotes the effective distribution of material and resources and increases mobility of people. However, the transportation sector is an important and increasing contributor to greenhouse gas emissions and its proportion of CO_2 emissions is growing in all areas of the world (Cai et al., 2012; Liu et al., 2016; Saboori et al., 2014; Xu and Lin, 2015). The global transportation sector is the second largest sector of greenhouse gas (GHG) emissions, second only to the power generation sector. It accounts for 24% of the total global direct CO_2 emissions from fuel combustion (IEA, 2020a). In practice, the realization of the national overall emission reduction target is actually the realization of the emission reduction target of each source within each industry. In 2020, the State Council of China issued a white paper titled "Sustainable Development of China's Transport", proposing that the transport industry will comprehensively promote energy conservation, emission reduction and low-carbon development. As one of the main sources of carbon dioxide emission, the study on the carbon emission of transportation sector (TCE) has always been concerned (Cai et al., 2012; Tian et al., 2014; Wang et al., 2017; Zhang and Wei, 2015). The carbon emissions of China's transportation industry increased from 260 mt (million tons) in 2000 to 889 mt in 2017, an increase of 241.92% compared with 2000. Therefore, it is urgent for China's transportation industry to reduce emissions. By accurately predicting CO_2 emissions, scholars can provide theoretical grounding for policy makers and improve the management level of carbon emissions (Qiao et al., 2020).

A large number of scholars have predicted future carbon emissions through a variety of prediction models. However, the projections of future CO_2 emissions from these models are based on a large amount of data. In case of less data or smaller samples, the following scholars used the grey model (GM) to predict the future carbon emissions, most of which are based on one order single variable grey model (GM(1,1)) and one order multiple variable grey model (GM(1,N)). Şahin (2019) used metabolic GM(1,1), nonlinear metabolic GM(1,1), optimized metabolic GM(1,1), and optimized nonlinear metabolic GM(1,1) to estimate Turkey's GHG emissions. But his research could not be used for long-term predicting, nor did it take into account changes in population and GDP. Through the transformation model of GM(1,N), non-linear GM(1,N) and the non-linear GM(1,N) of transformed form (TNGM(1,N)), Wang and Ye (2017) calculated the optimal value of the parameters that could reflect the nonlinear effect through the optimization algorithm. After comparison, he found that the TNGM(1,2) model had the highest prediction accuracy. Xu et al. (2019) combined adaptive GM(1,1) with buffer rolling method to predict future greenhouse gas emissions. Compared with traditional models, this model improved the adaptability of data characteristics and prediction accuracy. Huang et al. (2019) predicted the CO_2 emissions of China through a combination of grey relational analysis, long short-term memory method and principal component analysis. By using the combined model of Verhulst model, GM(1,1) and system cloud GM(1,1), Zhang et al. (2015) predicted the TCE in Shandong. The results showed that the combined grey model was more accurate than the single prediction model. By using the same idea, Wu (2017) established the grey combined model of urban road traffic carbon emission, which verified this model. Song (2018) used GM(1,1), partial least squares regression model, grey Markov model and GM(1,N) model to predict the CO_2 emissions of traffic. The results showed that grey Markov model had the highest prediction accuracy compared with other three models.

At present, some scholars have studied the fractional order grey prediction model in different fields. Fang et al. (2013) used fractional order accumulation grey system model (FGM(1,1)) to predict the maintenance cost of small sample weapon system. The empirical results showed that FGM(1,1) could predict the memory process. Wu et al. (2013) proposed a new fractional order accumulation grey system model. In the in-sample model, when the accumulation order becomes small, it can better reflect the priority of new information. However, when the accumulation order number is 0, the grey system model cannot handle the system with memory. The empirical results showed that the new grey model had a very significant predictive performance. Wu et al. (2018) used the fractional accumulation GM(1,1) model (FGM(1,1)) to predict the annual average concentrations of $PM_{2.5}$, PM_{10}, SO_2, NO_2, 8-h O_3, and 24-h O_3 in the Beijing-Tianjin-Hebei region from 2017 to 2020. Wu and Zhao (2019) used fractional order accumulation GM(1,1) model to forecast the number of light pollution days and the annual average concentration of $PM_{2.5}$ in the Beijing-Tianjin-Hebei region in 2020. Jiang et al. (2020) proposed fractional order accumulation nonlinear grey multivariable model (NFGM(1,N)). In terms of prediction performance, the prediction accuracy of NFGM(1,N) model is better than ARMA model, linear regression model, GM(1,1) model, GM(1,N) model and FGM(1,N) model. Şahin (2020) studied the prediction accuracy of fractional nonlinear grey Bernoulli model (FANGBM(1,1)) and its simplified forms, and used FANGBM(1,1) with relatively high prediction accuracy to predict the total installed capacity and power generation of renewable energy and hydroelectric energy in Turkey from 2019 to 2030. Xu et al. (2020) selected three indexes of GDP, PCDIIP-rh and total population to study the influence of sample length on the prediction validity of FGM(1,1) model. The results showed that the prediction of 4-6 samples is the most suitable. Şahin (2021) proposed a new optimized fractional nonlinear grey Bernoulli model, referred to as OFANGBM(1,1).The model used genetic algorithm to optimize the background value λ, the power index value γ and the fractional order value r.

In recent years, some scholars have studied the prediction of carbon emission intensity through various research methods. Wang et al. (2014) established a hybrid nonlinear grey prediction and quota allocation model (HNGP-QAM) to support the optimization planning of China's provincial and departmental carbon intensity reduction in 2020. At such a dual level, HNGP-QAM is not only helpful to predict carbon intensity and its fluctuation in the relevant period, but also helpful to determine China's 2020 carbon intensity reduction target and corresponding quotas, so as to minimize the total cost of emission reduction. Ren and Guo (2016) used GM(1,1) model and linear regression model to forecast the total energy consumption in 2020 and 2030. Then, the carbon emission intensity is calculated to analyze the realization of China's carbon emission reduction target. The results showed that some of China's commitments to carbon intensity were not actually binding, and policy intervention is needed to achieve China's 2030 carbon emission peak and carbon intensity reduction targets. Dong et al. (2018) used structural decomposition analysis (SDA) and quantile regression analysis to study the driving factors of carbon emission intensity change in China. Based on input-output SDA, the carbon emission intensity of China from 1992 to 2012 was decomposed from the perspectives of economic aggregate and economic sector. The results showed that the industrial sector was the key sector of energy conservation and emission reduction.

In all, there were many scholars who predicted the future carbon emissions, but there were few researches on the carbon emission of transportation sector (TCE), especially those using the combined model based on the grey prediction system to predict the TCE. The innovation of this paper lies in the introduction of fractional order model and Markov model on the basis of GM(1,1). By comparing the prediction accuracy before and after the model improvement, we used the better optimized prediction model to predict the carbon emission intensity of transportation sector (TCEI). The paper aims to provide a theoretical basis for policymakers' decisions on whether China's transportation sector will be able to meet its emission reduction target, which calls for a 60% to 65% reduction in carbon emission intensity from 2005 levels by 2030. It also provides theoretical support for the transportation department to evaluate the implementation effect of the current emission reduction work and to formulate more effective energy-saving and emission reduction strategies in the future.

The layout of the paper is organized as follows. In Section 2, we introduce GM(1,1) (Model 1), fractional order GM(1,1) (Model 2), the combination model of GM(1,1) and Markov model (Model 3) and the combination model of fractional order GM(1,1) and Markov model (Model 4). In Section 3, we explain the data sources of this study. In Section 4, we calculate the prediction accuracy of Model 1-4. We summarize and compare the prediction accuracy of several models. Then, we get the prediction model with the highest accuracy and use this model to predict the future TCEI in China. Based on these projections, we calculate the future TCEI targets for China. At the same time we put forward some policy suggestions. In Section 5, we summarize the results of model improvement, the innovation and limitations of the paper research, and then introduce the direction of further research.

2. Methodology

As mentioned above, many scholars have studied the carbon emissions of various industries through the grey model. GM(1,1) is an exponential growth model, which is mainly aimed at the univariate system and seeks for the change rule of the system through the randomness of the weakening sequence generated by accumulation, so as to establish a prediction model about time. FGM(1,1) can effectively improve the prediction accuracy of GM(1,1) by extending the model order from positive integers to positive real numbers. The prediction accuracy of FGM(1,1) can be improved by selecting the appropriate order of accumulation. Markov model is to predict the state of the future system through the current state and state transition rule. This model can be used to solve the problem with large random fluctuation, so it can be used to make up for the deficiency of grey model (Li et al., 2020d).

2.1. Grey model

The modeling idea of the grey model is to directly transform the time series into continuous differential equations, so as to establish the development dynamic change model of the abstract system. This kind of prediction can better observe the internal law of the system and predict the future development trend of the system. The commonly grey model is GM(1,1) (Wang et al., 2014) and the modeling steps can generally be summarized as Eqs. (1)-(6).

Assuming that the sequence $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \cdots, x^{(0)}(n))$

among them, $x^{(0)}(k) \ge 0,\ \ k=1,2,\cdots,n$. $X^{(1)}$ is the 1-AGO sequence of $X^{(0)}$, then it is valid Eq. (1):

$$X^{(1)} = (x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)) \tag{1}$$

where $x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i),\ \ k=1,2,\cdots,n$ ·

The whitening differential equation is shown as Eq. (2):

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b \tag{2}$$

The parameter vector $\hat{a} = [a,b]^T$ in Eq. (2) can be estimated by the least square method. It is shown as Eqs. (3-4):

$$\hat{a}=(B^{T}B)^{-1}B^{T}Y \tag{3}$$

$$Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix},\quad B=\begin{bmatrix} -\frac{1}{2}\left[x^{(1)}(1)+x^{(1)}(2)\right] & 1 \\ -\frac{1}{2}\left[x^{(1)}(2)+x^{(1)}(3)\right] & 1 \\ \vdots & \vdots \\ -\frac{1}{2}\left[x^{(1)}(n-1)+x^{(1)}(n)\right] & 1 \end{bmatrix} \tag{4}$$

Then the time response formula is Eq. (5):

$$\hat{x}^{(1)}(k)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)}+\frac{b}{a},\quad k=1,2,\cdots,n \tag{5}$$

The final reduction formula of GM(1,1) model is Eq. (6):

$$\hat{x}^{(0)}(k)=x^{(1)}(k)-x^{(1)}(k\text{-}1)=\left(1\text{-}e^{a}\right)\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)},\quad k=1,2,\cdots,n \tag{6}$$

2.2. Fractional order grey model

The GM(1,1) is an exponential growth model, which is mainly aimed at the univariate system. It looks for the change law of the system by generating the randomness of the weakening sequence by accumulation and establishes the prediction model about time on this basis. The fractional order contains an "in between" idea. The purpose of this paper is to select the appropriate accumulation order, which can improve the modeling accuracy of grey model. The structure of the FGM(1,1) is identical to that of the GM(1,1). The essential difference between them is that the GM(1,1) model uses the first-order accumulation of the original sequence $X^{(0)}$ to generate the sequence $X^{(1)}$ as the modeling sequence, while the FGM(1,1) uses the accumulation of r-order of the original sequence $X^{(0)}$ to generate the sequence as the modeling sequence, which presents a certain rule, and uses curve fitting to establish the mathematical model.

Assuming that the original non-negative series sequence is $X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\cdots,x^{(0)}(n))$, add r-order to the original sequence $X^{(0)}$ to get the sequence: $X^{(r)}=(x^{(r)}(1),x^{(r)}(2),\cdots,x^{(r)}(n))$, which can be gotten by Eq. (7) (Li et al., 2020d):

$$x^{(r)}(k)=\sum_{i=1}^{k}\frac{\Gamma(r+k-i)}{\Gamma(k-i+1)\Gamma(r)}x^{(0)}(i),k=1,2,\cdots,n. \tag{7}$$

Assuming that $x^{(0)}(k)$ and $x^{(r)}(k)$, we can obtain Eq. (8),

$$x^{(0)}(k)+ax^{(r)}(k)=b. \tag{8}$$

Let's say that $X^{(r)}$ is fractional accumulation generates $X^{(0)}$ sequence.

$$Z^{(r)}=(z^{(r)}(2),z^{(r)}(3),\cdots,z^{(r)}(n))$$

among them, $z^{(r)}=\frac{x^{(r)}(k)+x^{(r)}(k\text{-}1)}{2}$, $k=2,3,\cdots,n$, then, we can get Eq. (9):

$$x^{(r-1)}(k)+az^{(r)}(k)=b \tag{9}$$

This model is the first-order differential equation of $X^{(r)}$, and the sum of the r-order of $X^{(0)}$ is used to generate the mean value of the sequence $X^{(r)}$ and the $Z^{(r)}$ after mean value processing is used as the modeling data. $X^{(r)}$ is reduced to the predicted value of the original data $X^{(0)}$ after r-order reduction, and this model is called FGM(1,1). $X^{(-r)}=(x^{(-r)}(1),x^{(-r)}(2),\cdots,x^{(-r)}(n))$ is the r-order degenerate generation operator of $X^{(0)}$, which can be calculated by Eq. (10):

$$x^{(-r)}(k)=\sum_{i=0}^{k-1}(-1)^{i}\frac{\Gamma(r+1)}{\Gamma(r-i+1)\Gamma(i+1)}x^{(0)}(k-i),k=1,2,\cdots,n. \tag{10}$$

The parameter vector $\hat{a}=[a,b]^{T}$ in Eq. (9) can be estimated by the least square method. It is shown as Eq. (11):

$$\hat{a}=(B^{T}B)^{-1}B^{T}Y \tag{11}$$

Among, $Y=\begin{bmatrix} x^{(r-1)}(2) \\ x^{(r-1)}(3) \\ \vdots \\ x^{(r-1)}(n) \end{bmatrix},\quad B=\begin{bmatrix} -z^{(r)}(2) & 1 \\ -z^{(r)}(3) & 1 \\ \vdots & \vdots \\ -z^{(r)}(n) & 1 \end{bmatrix}$ and $x^{(r-1)}(k)=x^{(r)}(k)-x^{(r)}(k\text{-}1)$, $k=2,3,\cdots,n.$

Then, we have Eq. (12),

$$\frac{dx^{(r)}}{dt}+ax^{(r)}=b, \tag{12}$$

which is the whitening differential equation of $x^{(r-1)}(k)+az^{(r)}(k)=b$ in FGM(1,1).

The time response expression of $x^{(r-1)}(k)+az^{(r)}(k)=b$ in FGM(1,1) is Eq. (13):

$$\hat{x}^{(r)}(k)=\left[x^{(0)}(1)-\frac{b}{a}\right]e^{-a(k-1)}+\frac{b}{a},\quad k=2,3,\cdots,n. \tag{13}$$

The reduction value of $\hat{x}^{(r)}(k)$ is Eq. (14):

$$\hat{x}^{(0)}(k)=\left(\hat{x}^{(r)}\right)^{(-r)}(k)=\sum_{i=0}^{k-1}(-1)^{i}\frac{\Gamma(r+1)}{\Gamma(r-i+1)\Gamma(i+1)}\hat{x}^{(r)}(k-i),k=2,3,\cdots,n$$
$$\hat{x}^{(0)}(1)=x^{(0)}(1) \tag{14}$$

The FGM(1,1) obtain the r-order prediction data through the time response function, then reduce it to the simulation data through the r-order reduction, and finally substitute the optimal r-order into the model. The optimal order of FGM(1,1) is obtained by particle swarm optimization algorithm (PSO). PSO algorithm is a global optimization algorithm proposed by Kennedy Eberiiart in 1995. In order to improve the global convergence, the PSO algorithm of adaptive variation of population fitness variance is adopted in this paper to obtain the minimum mean absolute percentage error in the FGM(1,1), at which time the order of the prediction model is the optimal order.

The objective function is given by Eq. (15):

$$\min f(r)=\frac{1}{n-1}\sum_{k=2}^{n}\frac{\left|x^{(0)}(k)-\hat{x}^{(0)}(k)\right|}{x^{(0)}(k)}, r\in R^{+}. \tag{15}$$

The operating parameters of PSO are set as follows:

(1) Learning factor c_1=2, c_2=2;
(2) Dynamic inertia weight factor w=0.8;
(3) The maximum number of iterations is 300;
(4) Particles in the range $r\in[0,2]$;
(5) The number of individuals in the group is;
(6) Accuracy is set to 0.000001.

2.3. Markov model

Andrei Markov proposed the Markov chain in 1906. At present, Markov model is widely used in engineering technology, natural science and public utilities (Ren and Gu, 2016).

2.3.1. State interval division

Based on the value range *s* of the relative ratio *q* about the actual value and the predicted value calculated above, markov state interval is divided. Divide the equal length of the value range of *p* into *n* intervals to obtain *n+1* state boundary value $s=(s_1,s_2,\cdots,s_{n+1})$, where *n* is the number of state intervals.

Then the state interval E_i is divided as Eq. (16):

$$\begin{cases} E_1=\left[s_1\hat{x}^{(0)},s_2\hat{x}^{(0)}\right] \\ \quad\vdots \\ E_n=\left[s_n\hat{x}^{(0)},s_{n+1}\hat{x}^{(0)}\right] \end{cases} \tag{16}$$

2.3.2. Construct k-step state transition probability matrix

Let M_{ij} represent the original sample number of state E_i transferred to state E_j after k steps. M_i is the sample number of state E_i, and $P_{ij}(k)$ is the probability of data sequence which transferred from state E_i to state E_j through *k* steps. Among them, $P_{ij}(k)$ is calculated by Eq. (17).

$$P_{ij}(k)=\frac{M_{ij}(k)}{M_i}(i=1,2,\cdots,n) \tag{17}$$

Let k-step state transition probability matrix be *P*(k), which is calculated by Eq. (18):

$$P(k)=\begin{bmatrix} P_{11}(k) & P_{12}(k) & \cdots & P_{1n}(k) \\ P_{21}(k) & P_{22}(k) & \cdots & P_{2n}(k) \\ \vdots & \vdots & \cdots & \vdots \\ P_{n1}(k) & P_{n2}(k) & \cdots & P_{nn}(k) \end{bmatrix} \tag{18}$$

2.3.3. Calculate the grey Markov prediction value $\hat{x}'^{0}$

Using the state k-step transition probability matrix P(k), it can be calculated that the corresponding probability of transferring $\hat{x}'^{(0)}$ to state interval $E_i=(E_1,E_2,\cdots,E_n)$ is $P_i=(P_1,P_2,\cdots,P_n)$, and the state interval E_{max} corresponding to P_{max} is taken as the last state interval of $\hat{x}'^{(0)}$.

The grey Markov predictive value $\hat{x}'^{0}_{t+1}$ can be obtained by taking the median of the state interval. It is shown as Eq. (19):

$$\hat{x}'^{(0)}_{t+1}=\frac{(s_i+s_{i+1})\hat{x}^{(0)}_{t+1}}{2} \tag{19}$$

2.4. Model construction

This paper combines FGM(1,1) and Markov model to obtain a new combination model, whose modeling ideas is shown in Fig. 1. Among them, PSO algorithm is solved by MATLAB software.

2.5. Accuracy indicators

It is necessary to evaluate the accuracy of the prediction results respectively. The evaluation indicators are calculated by residual $e^0_{(t)}$ and relative error $q_{(x)}$. Its calculation formula is given by Eq. (20):

$$e^0_{(t)}=x^0-\hat{x}^0_{(t)}, q_{(x)}=\frac{e^0_{(t)}}{x^0} \tag{20}$$

The mean absolute percentage error (MAPE) can be used to compare the prediction accuracy of various models (Şahin, 2019). The calculation formula of MAPE is according to Eq. (21):

$$MAPE=\frac{\sum_{x=1}^{n}\left|q_{(x)}\right|}{n}\times 100 \tag{21}$$

The carbon emission intensity is calculated by Eq. (22) (Chen, 2011):

$$Y_j=\frac{E_j}{G_j} \tag{22}$$

where: Y_j is the TCEI in year *j*, E_j is the TCE in year *j*, and G_j is the GDP of transportation sector in year *j*.

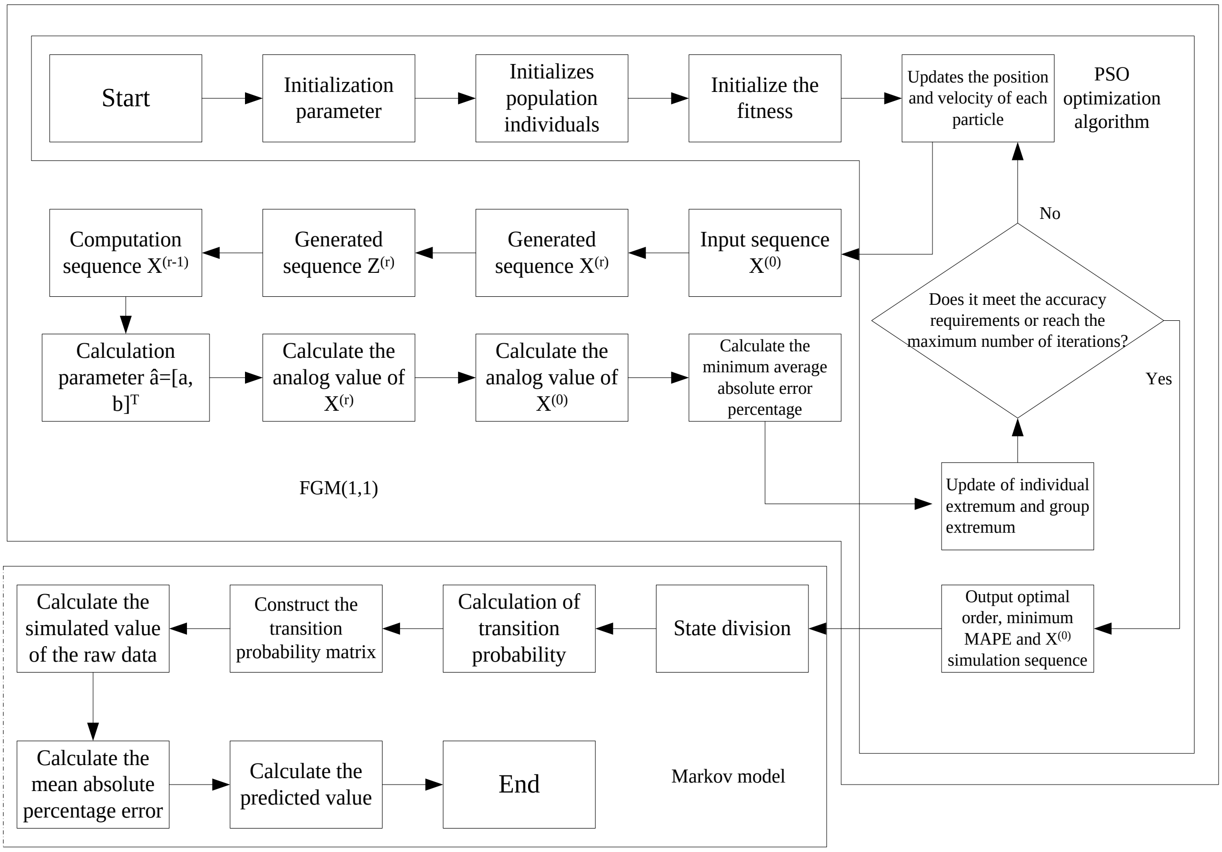

Fig. 1. The framework of FGM(1,1)-Markov model

3. Data sources

The data are from the International Energy Agency (IEA, 2020b) and China statistical yearbook (National Bureau of Statistics, 2020). This paper collected data on carbon dioxide emissions and GDP of China's transportation sector from 2000 to 2017. The specific data is shown in Table 1.

Table 1. The original data about CO_2 emissions and GDP in the transportation sector

year	*TCE (mt)*	*GDP (100 million yuan)*
2000	260	6162
2001	264	6871
2002	284	7494
2003	321	7915
2004	376	9307
2005	403	10669
2006	440	12186
2007	474	14605
2008	512	16368
2009	524	16522
2010	575	18784
2011	628	21842
2012	692	23763
2013	748	26043
2014	777	28501
2015	834	30488
2016	851	33059
2017	889	37173

4. Empirical research

4.1. Prediction accuracy analysis

Through the calculation of Model 1-4, the calculated parameters of each model were obtained, and the simulation values and relative errors calculated by each model were obtained (Figs. 2-9). Table 2 shows the relevant parameters of the calculation process of each model.

Table 2. Relevant parameters in the calculation process of each model

	model	*a*	*b*	*r*
TCE	Model 1,3	-0.0713	273.3316	1
	Model 2,4	-0.0242	64.2013	0.2591
GDP	Model 1,3	-0.1010	6605.6279	1
	Model 2,4	-0.0761	874.4893	0.1544

As can be seen from Figs. 2-9, for TCE and GDP in the transportation sector, the fitting effect of Model 2 and Model 3 is obviously better than that of Model 1, and the relative error is smaller. Moreover, the prediction accuracy of Model 4 is further improved on the basis of Model 2 and Model 3.

In the above diagram, Fig. 5 and Fig. 9 are the fitting diagram of Model 4. In Fig. 5, the relative errors of 2005, 2009 and 2015 are larger than those of other years. In Fig. 9, the relative errors of 2008, 2009 and 2011 are also larger than those of other years.

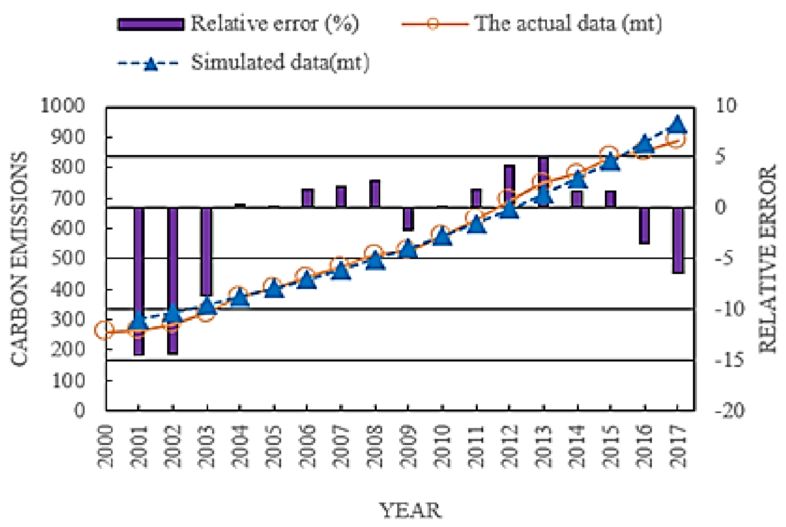

Fig. 2. Model 1: TCE (mt)

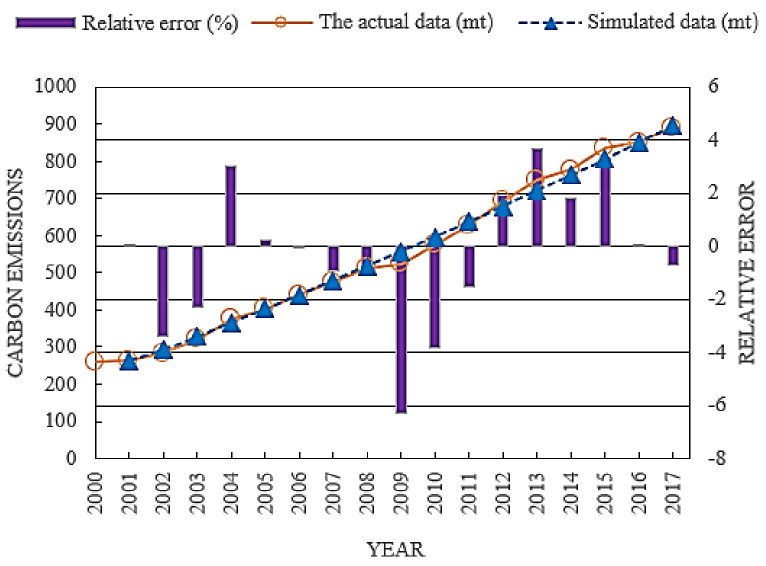

Fig. 3. Model 2: TCE (mt)

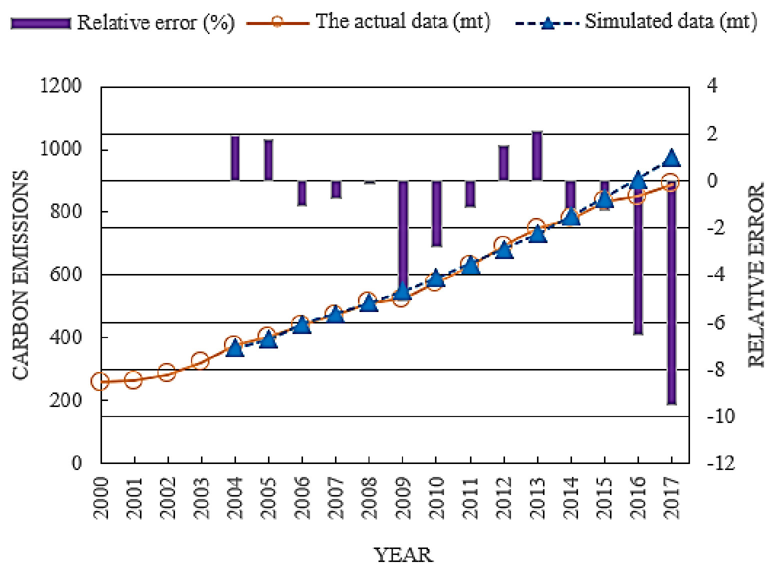

Fig. 4. Model 3: TCE (mt)

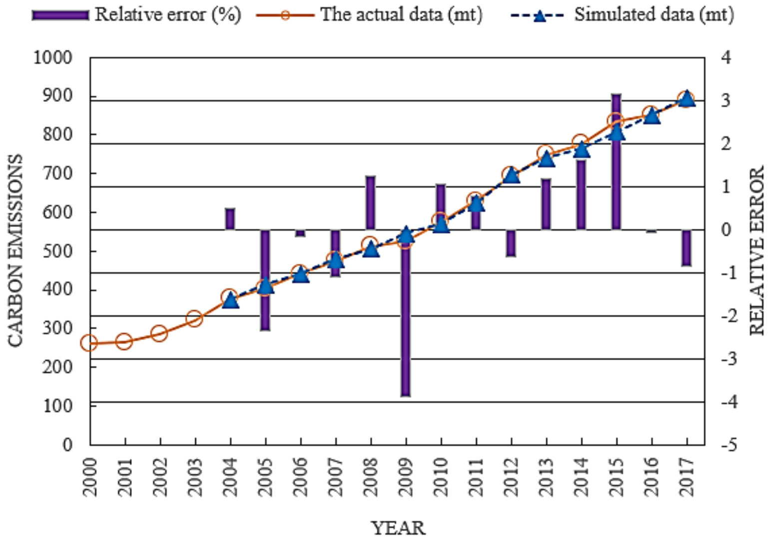

Fig. 5. Model 4: TCE (mt)

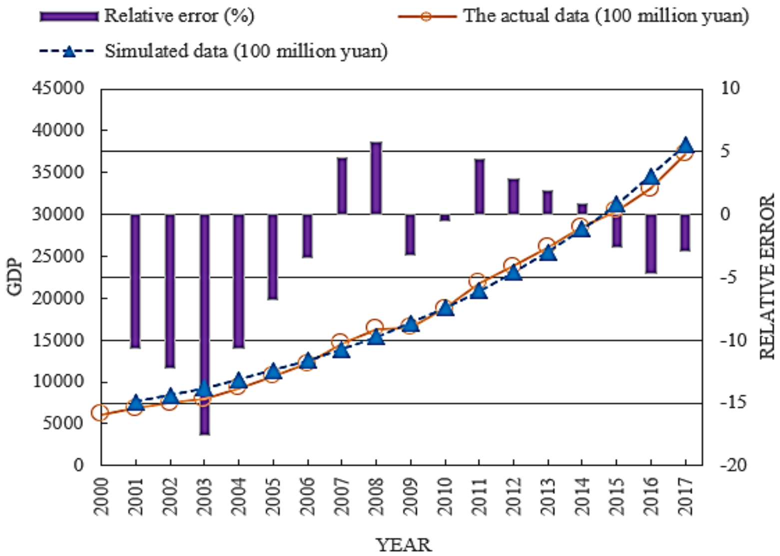

Fig. 6. Model 1: GDP in the transportation sector (100 million yuan)

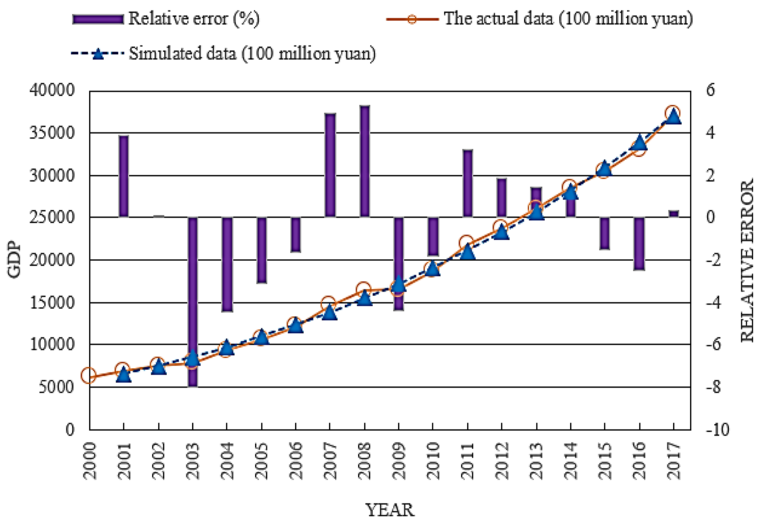

Fig. 7. Model 2: GDP in the transportation sector (100 million yuan)

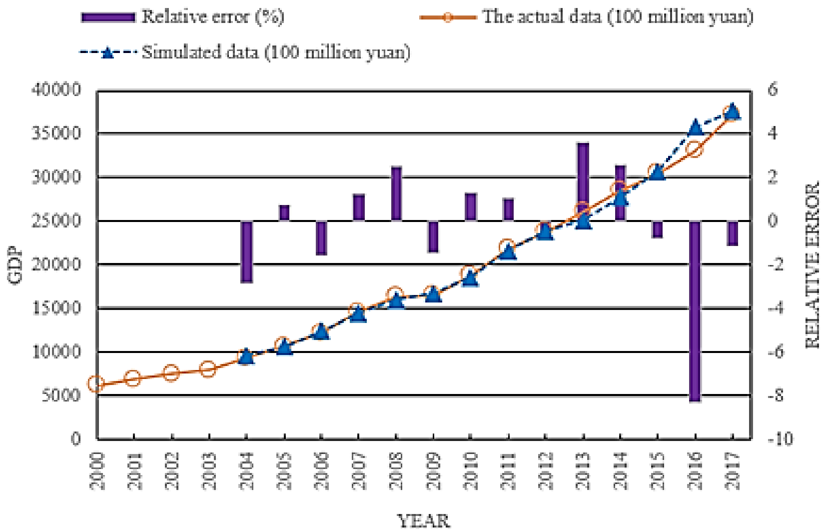

Fig. 8. Model 3: GDP in the transportation sector (100 million yuan)

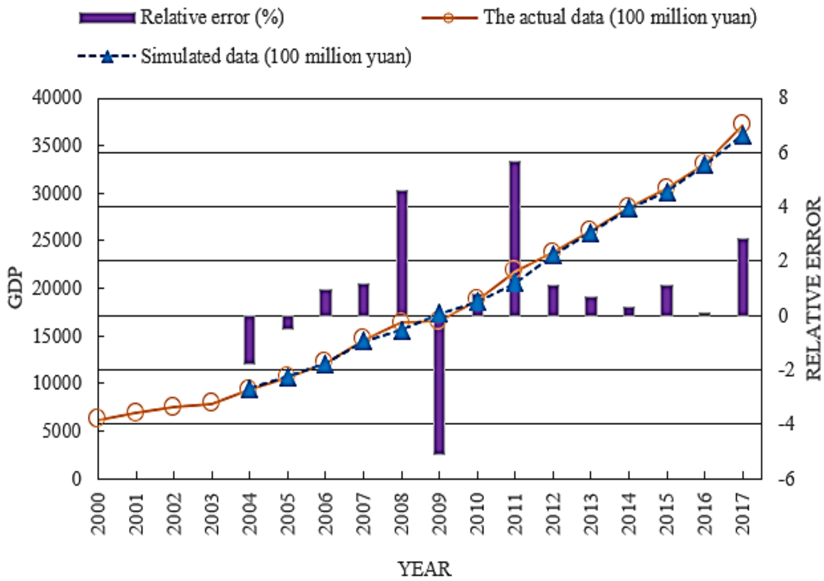

Fig. 9. Model 4: GDP in the transportation sector (100 million yuan)

After observation, it is found that the transition probability of a certain state in these samples is not much different or even equal to the maximum transition probability. Therefore, the reason for the relative errors of these samples are large is that the Markov model only uses the state interval with the largest transition probability to correct the fitted value, but the probability of other state intervals is not all zero. Therefore, the model does not make full use of the state transition probability information contained in the original data. This needs to be further improved. To facilitate the analysis, the prediction accuracy of the above models is summarized and compared according to Eqs. (20-21), as shown in Table 3.

Table 3. The comparison table of each model MAPE

model		*Model 1*	*Model 2*	*Model 3*	*Model 4*
MAPE	**TCE**	4.1868	2.0007	2.6127	1.3261
	GDP	5.6191	2.8938	2.1175	1.9090

After comparison, it can be found that the MAPE of the Model 4 is lower than those of Model 1-3. In consequence, the use of Model 4 will further reduce the MAPE and further improve the prediction accuracy.

4.2. Prediction

We use Model 4 to predict China's TCE and GDP of the transport sector from 2018 to 2030 (as shown in Table 4), and thus calculate the TCEI. The TCEI for 2005 and 2030 are shown in Table 5.

As a result, the TCEI of China was projected to decrease by 63.70% in 2030 compared to 2005, but one of China's targets under the Paris agreement signed in 2015 is to reduce carbon emission intensity by 60-65% by 2030 compared with 2005 levels. In consequence, under the current emissions reduction measures and intensity, China's transport sector will be able to meet the minimum emission reduction targets promised, but it will be difficult to achieve the maximum emission reduction targets by 2030.

Table 4. Forecast result: China's TCE and GDP in transportation sector

year	*TCE*	*GDP in the transportation sector*
2018	942	40769
2019	965	44485
2020	1011	46926
2021	1111	51108
2022	1161	55617
2023	1184	64516
2024	1235	67919
2025	1288	73766
2026	1308	80073
2027	1362	84072
2028	1486	91174
2029	1545	98836
2030	1566	114246

Table 5. TCEI (Ton /10,000 RMB)

2005	*2030*	*Decreased*
3.7774	1.3710	63.70%

TCEI is calculated through TCE and GDP of the transport sector, so the development trend of TCEI can be adjusted by controlling the future TCE and GDP of the transport sector. Moreover, since economic development is related to the national economy and people's livelihood, TCE is the main target of government regulation. In order to achieve the maximum reduction goal of reducing China's carbon emission intensity by 65% from 2005 levels by 2030, we calculated that China's transportation sector would have to reduce its carbon emission intensity by at least 2.18% annually from 2017 if GDP growth trend remains unchanged. In other words, the TCEI of China will have to drop by at least 0.0823 tons/10,000 yuan per year from 2017, so we have the development goals that TCEI must meet in the future. Combined with the emission reduction target that TCEI must achieve in the future and the future development of GDP of the transportation industry predicted above, the development trend of China's TCE after 2017 can be calculated, as shown in Table 6.

Table 6. Forecasting results of China’s TCE by Model 4

year	*TCE(mt）*
2018	941
2019	991
2020	1006
2021	1054
2022	1101
2023	1224
2024	1233
2025	1279
2026	1322
2027	1319
2028	1355
2029	1388
2030	1510

If the development trend of China's TCE in Table 6 is met, China's transportation sector could achieve a 65% reduction in carbon emission intensity by 2030 compared with 2005.

4.3 Discussion

Through the comparison of prediction accuracy, it is found in this paper that the prediction accuracy of Model 4 is the highest among the four prediction models mentioned above. Based on Model 4, the MAPE of TCE and the GDP of transportation sector are 1.3261% and 1.9090% respectively. In the field of carbon emissions, some scholars have studied the improvement of the prediction accuracy of many models. Among them, the adaptive grey model with buffered rolling mechanism (Xu et al., 2019), the general regression neural network based on the correlation analysis (Antanasijević et al., 2014), the optimized nonlinear metabolic grey model (Şahin, 2019) and the improved Gaussian process regression based on modified PSO algorithm model (Fang et al., 2018) calculated the MAPE as 2.81%, 3.60%, 5.19% and 8.00% respectively. The MAPE of Model 4 constructed in this paper is lower than the above models, so Model 4 has better carbon emission prediction performance.

In order to meet the maximum emission reduction targets, China needs to actively launch more aggressive emission reduction policies and intensify emission reduction efforts. For the transportation sector, CO_2 emissions can be reduced through the following measures:

(1) Optimize energy structure and develop new energy vehicles

With the development of traffic, the optimization of energy consumption structure is the key to reducing CO_2 emissions. China should further highlight the application and study of energy technology and the implementation of emission reduction policy. Currently, most of the vehicles in China are still powered by fossil fuels. For example, the share of biofuels in China's transportation sector in transportation energy consumption increased from 1,962,766 ktoe in 2000 to 2,821,408 ktoe in 2017, only increasing by 43.75% in 18 years (IEA, 2020a). To decrease energy consumption and TCE, authorities should vigorously develop clean energy vehicles that replace fossil fuels. And China should promote the research of new technology, accelerate vehicle upgrading and replace high energy consumption and pollution in time. Governments should increase investment in cleaner energy research and the construction of infrastructure. And China needs to complete its law and policy system of energy gradually to create a healthy environment for the development of low-carbon transportation.

(2) Develop public transportation

China should vigorously develop the public transportation systems of electric and hybrid energy, and decrease CO_2 emissions from the widespread use of transportation. China's urbanization is characterized by rapid urban and rural migration for better jobs and the disorderly expansion of urban, as well as private car ownership growing at an average annual rate of more than 20 percent. It has led to a series of challenges for many Chinese cities, such as resource shortage, traffic congestion and increased carbon dioxide emissions. Public transport has the comparative advantages of large capacity, high efficiency, low energy consumption and low carbon emissions (Ministry of Transport of the People's Republic of China, 2016). In consequence, it is beneficial for China to develop a public transport system of electric and hybrid energy and decrease CO_2 emissions from the widespread use of transportation. In addition, China should further increase the investment in infrastructure, especially conventional public traffic and rail traffic, and promote public transportation and rail transportation gradually, which can effectively solve the traffic problem.

(3) Improve the efficiency of energy and promote low-carbon technologies in the industrial chain

Improving energy efficiency remains an effective way for China to reduce CO_2 emissions. China needs to set up a long-term energy conservation mechanism and shut down the outdated production capacity in energy-intensive industries. In addition, China needs to optimize the industrial structure and enhance the technological level for the increase of energy efficiency, especially in the transportation sector. The total energy consumption of China's transportation sector increased from 99.16 million tons of standard coal in 2000 to 421.91 million tons of standard coal in 2017, an increase of 325.48 percent (National Bureau of Statistics, 2020). China should promote low-carbon technologies in the industrial chain to fully realize the potential of carbon emission efficiency. Technological advance has a positive impact on carbon emission efficiency and a strong industrial radiation effect. The government needs to increase the investment in technology, introduce advanced and mature technologies in the industrial chain, and enhance the promotion of low-carbon technologies, such as cultivating a carbon trading market.

(4) Restrictions on private cars

Economic development will inevitably bring pressure to the environment, but the final objective is to achieve the synchronous development of economy and low-carbon transportation. With the improvement of people's economic ability, the number of private cars has been on the rise as people's increasing purchasing power has changed their preference for travel. People prefer convenient but not environmentally friendly modes, such as private car. The number of private cars in China soared from 6.2533 million in 2000 to 185.1511 million in 2017, an increase of 2,860.85 percent (National Bureau of Statistics, 2020). The government should take some measures to guide people to choose a low-carbon way to travel. For private cars, on the premise of convenience, China should implement policies to control private cars, introduce relevant license plate restrictions and purchase restrictions, so as to reduce CO_2 emissions. Fuel taxes can guide consumer behavior, so further increases on fuel taxes and charges for vehicle emissions are other important economic tools to decrease fuel consumption and CO_2 emissions.

5. Conclusions

This paper aims to use a novel model to predict whether China's transportation sector can meet its emission reduction commitments under the Paris agreement. By comparing the accuracy of GM(1,1), FGM(1,1) and the GM(1,1)-Markov model, the results showed that FGM(1,1) and the GM(1,1)-Markov model were better than GM(1,1), which both improved the prediction accuracy. We combined the FGM(1,1) with the Markov model, and found that the MAPE were further reduced. In consequence, we chose the FGM(1,1)-Markov model to predict the future TCEI of China.

We concluded that China's transportation sector will emit 1.3710 tons of carbon emission intensity in 2030, compared with 3.7774 tons in 2005. As a result, the TCEI of China will be 63.70% lower in 2030 than in 2005. Under the current emissions reduction measures and intensity, China's transport sector will be able to meet the minimum emission reduction targets promised, but it will be difficult to achieve the maximum emission reduction targets by 2030. As time goes on, China must introduce effective measures to reduce carbon emission intensity as soon as possible. If TCEI of China drops by at least 0.0823 tons/10,000 yuan per year from 2017, China's transportation sector will achieve a 65% reduction in carbon emission intensity by 2030 compared with 2005. China needs to strengthen the management of TCE to meet the realization of its emission reduction commitment.

The innovation of this paper lies in the combination of FGM(1,1) model and Markov model to establish a new combined model, so as to predict the CO_2 of Chinese transport sector. But the research object of this paper is the carbon emission of Chinese transport sector, and the carbon emission contribution of different transport modes is not studied in detail. Therefore, this paper cannot provide more detailed policy suggestions to decision-makers to make their decisions more targeted.

In consequence, in future research, we can further study the carbon emission contribution of different transportation modes to make our policy recommendations more targeted. In addition, we can optimize the Markov model based on the FGM(1,1)-Markov model in the future, so as to further improve the accuracy of prediction model.

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