Nature Environment and Pollution Technology
An International Quarterly Scientific Journal

p-ISSN: 0972-6268 e-ISSN: 2395-3454	Vol. 16	No. 4	pp. 1293-1301	2017

Original Research Paper | Open Access

China's Carbon Emission Productivity and its Development Tendency from an Environmental Protection Perspective

Jian Jin†, Xiaoyi Ma and Yashuo Gao
School of Economics, Hebei University, Baoding 071000, China
†Corresponding author: Jian Jin

Nat. Env. & Poll. Tech.
Website: www.neptjournal.com

Received: 05-07-2017
Accepted: 08-09-2017

Key Words:
Environmental protection
Carbon emission productivity
Grey prediction model
Carbon dioxide
Methane

ABSTRACT

Burning coal, oil, natural gas and trees produce large amounts of carbon dioxide and methane. After these gases enter the atmosphere, the earth heats up and the carbon cycle becomes unbalanced, thereby resulting in global warming and deterioration of the ecological environment. To further analyse China's carbon emissions, this study calculated China's carbon emission productivity and predicted China's carbon emission productivity level and growth rate for a certain period. Results show that in 1990-2016, China's carbon emission productivity has continued to grow, and the actual GDP brought by unit carbon emissions has increased continuously. Moreover, China's carbon emission productivity is expected to continuously increase. China can increase carbon emission productivity by improving energy efficiency, formulating and implementing carbon budget programs at the micro level, and implementing carbon taxes. Here, we expand the research perspective of carbon emissions, which has a certain reference value to further study China's carbon emissions and protect the environment.

INTRODUCTION

In recent decades, global warming, ecological environment deterioration, and other issues have gradually elicited widespread concern. The Intergovernmental Panel on Climate Change (IPCC) data indicated that the global surface temperature has risen by 0.85°C since 1880. In 1981-1990, the global average temperature has risen by 0.48°C. Compared with 1850-1900, the global average surface temperature in 2003-2012 has risen by 0.78°C.

Many scientists believe that the greenhouse effect caused by a large amount of greenhouse gas emissions is the basic reason for global warming. Combustion of coal, oil, natural gas, and trees produce large amounts of carbon dioxide and methane, which heats the earth after entering the atmosphere and cause imbalance in the carbon cycle. The energy conversion form of the earth's biosphere changes. In 2011, concentrations of greenhouse gases, such as carbon dioxide, methane, and nitrous oxide reached 391 ppm, 1803 ppb, and 324 ppb respectively, which are respectively 40%, 150%, and 20% higher than those before the beginning of industrialization in the middle of the 18th century. Global warming caused by carbon emissions has already severely affected the production and daily life of humankind.

China's National Development and Reform Commission announced carbon emission reduction targets on November 4, 2014 and promised that by 2020, China's carbon dioxide emissions per unit of GDP would decrease by 40%-45% compared with 2005 levels. As a country with more than one billion people, economic growth and environmental protection must be considered simultaneously. To reduce carbon emissions while ensuring that the people's living standards and quality of life continue to improve, the best choice is to increase carbon emission productivity. By increasing carbon emission productivity, China can maintain stable economic growth and reduce carbon emissions simultaneously. Here, we study China's current carbon emission productivity level and its future development trends.

STATE OF THE ART

Given the deterioration of environmental conditions and the improvement of people's awareness of greenhouse effects and energy shortage, many research fields have begun to focus on the issue of carbon emission productivity; moreover, academic circles have focused on this issue in particular.

The earliest research on carbon emission productivity began with Kaya et al. (1997). They proposed that carbon productivity can be defined as the ratio of GDP to carbon dioxide emissions over a given period. This definition considers the performance of CO_2 from an economic perspective. Later generations called it narrow carbon emission productivity. Most scholars believe that the index of carbon productivity is an ideal index that can effectively combine the reduction of carbon emissions with economic growth

(Horbach 2008). Numerous other scholars have since studied carbon emission productivity from different angles on the basis of the Kaya (1997) research and achieved relatively rich results.

Based on literature review, the academic research on carbon emission productivity can be divided into four aspects. First, the significance of lifting carbon emission productivity is elaborated. Ernst & Young (2014) discussed the macroeconomic impacts of the low carbon transition. Mielnik (1999) and Beinhocker (2008) have confirmed that improving carbon emission productivity is highly significant for the economy and the welfare of society.

Second, the factors that affect carbon emission productivity are studied using several commonly used analytic procedures, such as the DEA model, Laspeyres decomposition method, and LMDI decomposition method. For example, the DEA model and panel data model were used by Zhang Lifeng (2013) to analyse factors that affect carbon emission productivity. Given the Laspeyres decomposition method, Lu Zhengnan et al. (2014) qualified how changes in the carbon emission productivity structure and the low-carbon technological progress affect the changes in China's carbon emission productivity.

Third, the differences in the carbon emission productivity among regions are discussed. For instance, Won-kyu & Kim (2010) studied the existing problems of carbon emission productivity among regions in Korea. Methods, such as cluster analysis, the Theil index, and the decoupling index, were used by Pan Jiahua et al. (2011) to analyse the different levels of carbon emission productivity in different regions.

Fourth, the challenges in improving carbon emission productivity are studied with certain corresponding policy recommendations to meet these challenges. The European Commission developed the roadmap to 2050 for establishing a low-carbon economy from multiple angles, such as the reform, innovation, and green development. Timmerman et al. (2014) provided a guide to enhance energy efficiency, reduce carbon emissions, and establish an industrial park. Based on comparisons among countries, He Jiankun et al. (2009) analysed the factors to improve carbon emission productivity and made additional efforts to propose relevant policy recommendations.

These studies have enriched the research system of carbon emission productivity from different perspectives and laid the foundation for further research. However, the existing research is mainly based on the status quo of carbon emission productivity in different countries. Research on carbon emission productivity forecast, on the future development trend of carbon emission productivity is lacking. Therefore, here, we take China as an example to study the prediction of carbon emission productivity to understand the future development trend of China's carbon emission productivity, and to provide a scientific basis for China to better maintain its energy saving and emission reduction, protect the environment, and maintain stable economic growth.

RESEARCH METHODOLOGIES

Data sources: All the data in this study are from the China Statistical Yearbook 2016 and the special statistics report of the National Bureau of Statistics of China. The chosen indexes comprise the nominal GDP (unit: CNY billion) between 1990 and 2016, the GDP index of base year 1978, and the total energy consumption, as well as the percentages of coal, crude oil, natural gas, hydropower, nuclear power, and wind power in the total energy consumption. Detailed data are given in Tables 1 and 2.

Basic theory of the GM (1, 1) model: Grey system has a portion of information in the system that is known, whereas the other part of the information is unknown, and uncertain relationships occur among various factors in the system. The grey system is widely found in social, economic, industrial, agricultural, ecological and biological fields. This system was proposed by Deng of the Huazhong University of Science and Technology from the late 1970s to the early 1980s. The grey system has been widely used since its creation (Chin-Tsai Lin et al. 2003, Cha'o-Kuang Chen et al. 1996, Che-Chiang Hsu et al. 2003).

The control, prediction, and decision-making have been the most active fields in applying the grey system theory. Because of its strong predictive power, this approach has been widely used in forecasting and prediction. The GM (1,1) model is the most commonly used forecasting or prediction model. Compared with other prediction methods, the biggest advantage of this model in forecasting depends on its serviceability for less primary data. If we fail to collect large amounts of data for various reasons, the methods of probability statistics cannot be used to find developing and changing rules. However, the GM (1,1) model can compensate for the shortcomings and allows prediction to proceed smoothly. Furthermore, the GM (1,1) model has two other advantages: its convenient computational method and its relatively high predictive accuracy. Accordingly, some researchers believe that the GM (1,1) model remains the first choice for decision-makers for certain cases of practical forecasting (Li Sifeng et al. 2000).

Steps of the GM (1,1) model: The numerical value of a random variable is known to be of certain volatility and randomness within a given time and range. Therefore, a set

Table 1: GDP and GDP index base year = 1978 in 1990-2016.

Year	GDP (CNY billion)	GDP index base year = 1978	year	GDP (CNY billion)	GDP index base year = 1978
1990	1887.29	281.9	2004	16184.02	1089.0
1991	2200.56	308.1	2005	18731.89	1213.1
1992	2719.45	351.9	2006	21943.85	1367.4
1993	3567.32	400.7	2007	27023.23	1562.0
1994	4863.75	453.0	2008	31951.55	1712.8
1995	6133.99	502.6	2009	34908.14	1873.8
1996	7181.36	552.5	2010	41303.03	2073.1
1997	7971.50	603.5	2011	48930.06	2270.8
1998	8519.55	650.8	2012	54036.74	2449.2
1999	9056.44	700.7	2013	59524.44	2639.2
2000	10028.01	760.2	2014	64397.40	2831.8
2001	11086.31	823.6	2015	68550.58	3027.6
2002	12171.74	898.8	2016	74412.72	3229.7
2003	13742.20	989.0			

Table 2: Total consumption of energy and its composition in 1990-2016.

Year	Total energy consumption (million tons of SCE)	Coal (%)	Crude oil (%)	Natural gas (%)	Hydro-power, nuclear power, wind power (%)
1990	987.03	76.2	16.6	2.1	5.1
1991	1037.83	76.1	17.1	2.0	4.8
1992	1091.70	75.7	17.5	1.9	4.9
1993	1159.93	74.7	18.2	1.9	5.2
1994	1227.37	75.0	17.4	1.9	5.7
1995	1311.76	74.6	17.5	1.8	6.1
1996	1351.92	73.5	18.7	1.8	6.0
1997	1359.09	71.4	20.4	1.8	6.4
1998	1361.84	70.9	20.8	1.8	6.5
1999	1405.69	70.6	21.5	2.0	5.9
2000	1469.64	68.5	22.0	2.2	7.3
2001	1555.47	68.0	21.2	2.4	8.4
2002	1695.77	68.5	21.0	2.3	8.2
2003	1970.83	70.2	20.1	2.3	7.4
2004	2302.81	70.2	19.9	2.3	7.6
2005	2613.69	72.4	17.8	2.4	7.4
2006	2864.67	72.4	17.5	2.7	7.4
2007	3114.42	72.5	17.0	3.0	7.5
2008	3206.11	71.5	16.7	3.4	8.4
2009	3361.26	71.6	16.4	3.5	8.5
2010	3606.48	69.2	17.4	4.0	9.4
2011	3870.43	70.2	16.8	4.6	8.4
2012	4021.38	68.5	17.0	4.8	9.7
2013	4169.13	67.4	17.1	5.3	10.2
2014	4258.06	65.6	17.4	5.7	11.3
2015	4300.00	64.0	18.1	5.9	12.0
2016	4360.00	62.0	18.3	6.4	13.3

of time-series data that meets the above features is unsuitable for establishing a prediction model. Even if the prediction model has been made, its prediction accuracy would be unsatisfactory. Nevertheless, we can transform the values into an ascending series with a strong regularity by analysing and processing the acquired data to prepare for the establishment of the prediction model in the future. In this study, the method of the Accumulated Generating Operation (AGO) was adopted to process the original series and set up the GM (1,1) model.

The differential equation of the GM (1,1) model is

$$\frac{dX}{dt}+aX=u \quad ...(1)$$

The following procedure is used to build the GM (1,1) model:

a. The measured original series is

$$X^{(0)}(t)=\left[X^{(0)}(1),X^{(0)}(2)\cdots X^{(0)}(n)\right] \quad ...(2)$$

b. The generated series can be obtained by the cumulative generation of the original series:

$$X^{(1)}(t)=\left[X^{(1)}(1),X^{(1)}(2)\cdots X^{(1)}(n)\right] \quad ...(3)$$

c. The system matrix B and Y_n are built.

$$B=\begin{bmatrix} -\left[X^{(1)}(1)+X^{(1)}(2)\right]/2 & 1 \\ -\left[X^{(1)}(2)+X^{(1)}(3)\right]/2 & 1 \\ \cdots & \cdots \\ -\left[X^{(1)}(n-1)+X^{(1)}(n)\right]/2 & 1 \end{bmatrix} \quad ...(4)$$

$$Y_n=\left[X^{(0)}(2),X^{(0)}(3)\cdots X^{(0)}(n)\right]^T \quad ...(5)$$

d. The parameter vector $\hat{\alpha}$ to be estimated is obtained.

The parameter vector in GM (1,1) model is $\hat{\alpha}=\begin{pmatrix} a \\ u \end{pmatrix}$, where a and u are constants and can be obtained by the least squares method:

$$\hat{a}=\left[B^TB\right]^{-1}B^TY_n \quad ...(6)$$

e. The form of the GM (1,1) model is determined.

$$\hat{X}^{(1)}(t+1)=\left[X^{(0)}(1)-\frac{u}{a}\right]e^{-at}+\frac{u}{a} \quad t=1,2,3\cdots n-1 \quad ...(7)$$

The formula above is the forecasting formula of the series.

f. The predicted value of original series is obtained.

Given that the formula predicts the value of the cumulative generation series, we can use the Lago method to obtain the predicted value of the original series. The formula is as follows:

$$\hat{X}^{(0)}(t)=\hat{X}^{(1)}(t)-\hat{X}^{(1)}(t-1) \quad ...(8)$$

Testing of the model results: If the fitting precision of the predicted series and the original series is relatively high, then extrapolative forecasting can be made (however, the reverse does not apply). Thus, the prediction accuracy of the model needs to be tested given the establishment of the prediction model. The test of the GM (1,1) model consists of the residual test, correlation test, and posterior variance test. These tests are explained below.

Residual test: $\hat{X}^{(1)}(t)$ can be predicted in accordance with above-mentioned prediction formula and we can turn it back into $\hat{X}^{(0)}(t)$ via the Inverse Accumulated Generating Operation (IAGO). Afterwards, the absolute error series and the relative error series between $\hat{X}^{(0)}(t)$ and $\hat{X}^{(1)}(t)$ can be separately obtained.

The absolute error series is

$$\Delta^{(0)}(t)=\left|X^{(0)}(t)-\hat{X}^{(0)}(t)\right| \quad t=1,2,3\cdots n \quad ...(9)$$

The relative error series is

$$\varphi(t)=\frac{\Delta^{(0)}(t)}{X^{(0)}(t)} \quad t=1,2,3\cdots n \quad ...(10)$$

The mean absolute error is

$$\overline{\Delta}^{(0)}=\frac{1}{n}\sum_{t=1}^{n}\Delta^{(0)}(t) \quad t=1,2,3\cdots n \quad ...(11)$$

The mean relative error is

$$\overline{\varphi}=\frac{1}{n}\sum_{t=1}^{n}\varphi(t) \quad t=1,2,3\cdots n \quad ...(12)$$

Correlation test: The correlation coefficient between $\hat{X}^{(0)}(t)$ and $\hat{X}^{(0)}(t)$ can be calculated by the grey correlation degree analysis to obtain the correlation degree.

The steps for the calculation of the degree of correlation are:

Step 1: Initialization. That is, $\hat{X}^{(0)}(t)$ divides the value of the series $\hat{X}^{(0)}(t)$ by its first value. $\hat{X}^{(0)}(t)$ can be obtained based on the above-mentioned approach.

$$X^{(0)}(t)'=\left(1,\frac{X^{(0)}(2)}{X^{(0)}(1)},\frac{X^{(0)}(3)}{X^{(0)}(1)}\cdots\frac{X^{(0)}(n)}{X^{(0)}(1)}\right) \quad ...(13)$$

$$\hat{X}^{(0)}(t)'=\left(1,\frac{\hat{X}^{(0)}(2)}{\hat{X}^{(0)}(1)},\frac{\hat{X}^{(0)}(3)}{\hat{X}^{(0)}(1)}\cdots\frac{\hat{X}^{(0)}(n)}{\hat{X}^{(0)}(1)}\right) \quad ...(14)$$

Step 2: Calculation of the difference between $\hat{X}^{(0)}(t)$ and $\hat{X}^{(0)}(t)$.

$$\Delta(t)=\left|\hat{X}^{(0)}(t)'-X^{(0)}(t)'\right| \quad ...(15)$$

Step 3: Calculation of the maximum and minimum of $\Delta(t)$.

$$M=\max(\Delta(t)) \quad ...(16)$$

$$m=\min(\Delta(t)) \quad ...(17)$$

Step 4: Calculation of the correlation coefficient.

$$r(t)=\frac{m+\rho\times M}{\Delta(t)+\rho\times M} \quad ...(18)$$

Step 5: Calculation of the degree of correlation.

$$R = \frac{1}{n}\sum_{t=1}^{n} r(t) \quad ...(19)$$

If the rule of thumb holds, the requirement is met, such that the degree of correlation is more than 0.6 when we define ρ as 0.5.

***Posterior variance test*:** The posterior variance test includes the variance ratio and the probability of small error, as described in the following procedure:

a. Calculation of the standard deviation of the original series is

$$S_1 = \sqrt{\frac{\sum\left[X^{(0)}(t) - \overline{X}^{(0)}\right]^2}{n-1}} \quad ...(20)$$

b. Calculation of the standard deviation of the absolute error series is

$$S_2 = \sqrt{\frac{\sum\left[\Delta^{(0)}(t) - \overline{\Delta}^{(0)}\right]^2}{n-1}} \quad ...(21)$$

c. Calculation of the variance ratio is

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

d. Calculation of the probability of small error is

$$P = P\left(\left|\Delta^{(0)}(t) - \overline{\Delta}^{(0)}\right| < 0.6745 S_1\right) \quad ...(23)$$

e. Test of the prediction accuracy:

We can obtain the variance ratio and the probability of small error with the above-mentioned steps. By referring to the table of accuracy test (Table 3), the accuracy of the prediction model may be estimated.

RESULTS ANALYSIS AND DISCUSSION

Calculation of China's real GDP in 1990-2016: Given that nominal GDP index contains price factors, it cannot truly reflect the level of economic development of a country. This study uses statistical methods to convert the GDP index of base year 1978 into GDP index of base year 1990. Upon this basis, the real GDP between 1990 to 2016 is deduced (Table 4).

Calculation of the carbon emission productivity: In this study, the computational formula of carbon emissions is:

$$C = \sum S_i \times F_i \times E \quad ...(24)$$

In this formula, C represents carbon emissions, which is measured in tons. The share of energy consumption of category i in the total energy consumption can be described by S_i. F_i indicates the carbon emission coefficient of energy i (primarily referring to coal, crude oil, and natural gas). Total energy consumption can be expressed by E, whose unit is 10000 tons of SCE. Carbon emission coefficients of various energies are presented in Table 5.

Table 3: Test table of model accuracy.

Rank	Mean relative error E	Variance ratio C	Probability of small error
Good	<0.01	<0.35	>0.95
Qualified	<0.05	<0.5	>0.8
Barely qualified	<0.1	<0.65	>0.7
Unqualified	>0.2	≥0.65	≤0.7

Table 4: China's real GDP in 1990-2016.

Year	Real GDP (CNY billion)	Year	Real GDP (CNY billion)
1990	1887.290	2004	7290.737
1991	2062.696	2005	8121.573
1992	2355.932	2006	9154.595
1993	2682.643	2007	10457.421
1994	3032.786	2008	11467.011
1995	3364.853	2009	12544.888
1996	3698.928	2010	13879.180
1997	4040.367	2011	15202.760
1998	4357.036	2012	16397.129
1999	4691.111	2013	17669.158
2000	5089.457	2014	18958.595
2001	5513.913	2015	20269.454
2002	6017.369	2016	21622.492
2003	6621.248		

Table 5: Carbon emission coefficients of various energies.

Type of energy	Coal	Crude oil	Natural gas
F_i (ton/10000 ton of SCE)	0.7476	0.5825	0.443

China's carbon emissions between 1990 and 2016 can be determined in terms of the data in Tables 2 and 5, as well as Equation (1), as given in Table 6.

Tables 4 and 6 show that China's real GDP has steadily increased during 1990-2016. At the same time, China's carbon emissions continue to grow.

Carbon emission productivity refers to the GDP created by one unit of carbon emissions. Carbon emission productivity (unit: CNY million/ton) between 1990 and 2016 can be calculated in accordance with the data of Tables 4 and 6, as shown in Table 7.

Table 7 shows that the carbon emission productivity between 1990 and 2016 has been gradually increasing with a steady growth tendency from CNY 28.30 million/ton in 1990 to CNY 82.87 million/ton in 2016, representing an average annual growth of 4.22%.

RESULTS AND DISCUSSION

Holistic modelling and analysis of results: The GM (1,1) model can operate on the data of carbon emission productivity between 1990 and 2016 and its prediction formula is as follows:

$$\hat{X}^{(1)}(t+1) = [X^{(0)}(1) - \frac{u}{a}]e^{-at} + \frac{u}{a} = 10.79e^{0.03t} - 10.51 \quad ...(25)$$

The mean absolute error of the measured series and the predicted series is 0.0375, the mean relative error is 0.0746, the variance ratio is 0.1695, the probability of small error is 1, the correlation degree is 0.5664, and the accuracy of the model is not high. We can also use the GM (1,1) model for prediction (Fig. 1).

Prediction accuracy of the model is low, and the prediction result is not desirable. Consequently, we must reject this prediction formula.

Segment modelling and analysis of results: Given the lower prediction accuracy of the GM (1,1) model, which was built based on the carbon emission productivity between 1990 and 2016, the ideal prediction interval for the predicting the carbon emission productivity in the coming years is needed. By observing the data of carbon emission productivity between 1990 and 2016, we divided them into three segments: 1990-1999, 2000-2009, and 2010-2016. The models were built separately to analyse the prediction accuracy of each prediction model and find the best GM (1,1) model.

The prediction accuracy of the GM (1,1) model, which was built based on the data of 1990-1999, 2000-2009, and 2010-2016, is shown in Figs. 2, 3 and 4, respectively.

A quick observation revealed that the prediction situation is better in the intervals of 1990-1999 and 2010-2016. The prediction accuracy of the model is tested further with the test index of every segment's model. The specific test indexes of every model are presented in Table 8.

Taken together, 2010-2016 is clearly the best interval for the establishment of the GM (1,1) model. Consequently, we chose the data from 2010 to 2016 to establish the model.

Establishment of the optimal GM (1, 1) model: The GM (1,1) model can be built considering the carbon emission productivity in 2010-2016; its prediction formula is:

$$\hat{X}^{(1)}(t+1) = [X^{(0)}(1) - \frac{u}{a}]e^{-at} + \frac{u}{a} = 9.49e^{0.06t} - 8.89 \quad ...(26)$$

Returning to the original series:

$$\hat{X}^{(0)}(t) = \hat{X}^{(1)}(t+1) - \hat{X}^{(1)}(t) \quad ...(27)$$

Prediction of carbon emission productivity in the next three years: China's carbon emission productivity between 2017 and 2019 can be predicted based on Equations (26) and (27). The results are given in Table 9.

Table 6: China's carbon emissions between 1990 and 2016.

Year	Carbon emission (ton)	Year	Carbon emission (ton)
1990	66690.58	2004	149894.90
1991	70301.68	2005	171348.13
1992	73830.33	2006	187681.98
1993	78050.44	2007	203784.29
1994	82291.72	2008	207394.76
1995	87575.87	2009	217243.81
1996	90090.26	2010	229521.51
1997	89780.18	2011	248889.24
1998	89770.10	2012	254310.06
1999	93043.06	2013	261391.49
2000	95526.89	2014	262735.76
2001	99937.39	2015	262314.41
2002	109312.73	2016	260929.21
2003	128515.20		

Table 7: Carbon emission productivity between 1990 and 2016.

Year	Carbon emission productivity (CNY million/ton)	Year	Carbon emission productivity (CNY million/ton)
1990	28.30	2004	48.64
1991	29.34	2005	47.40
1992	31.91	2006	48.78
1993	34.37	2007	51.32
1994	36.85	2008	55.29
1995	38.42	2009	57.75
1996	41.06	2010	60.47
1997	45.00	2011	61.08
1998	48.54	2012	64.48
1999	50.42	2013	67.60
2000	53.28	2014	72.16
2001	55.17	2015	77.27
2002	55.05	2016	82.87
2003	51.52		

The forecast results show that China's carbon emission productivity will continue to increase in the future. The average annual growth rate of China's carbon emission productivity was 4.22% in 1990-2016. Compared with the average annual growth rate since 1990, the annual growth rate in the future remains increasing. However, compared with 2010-2016, the growth rate has decreased slightly. This result indicates that since 1990, the various measures taken by the Chinese government have played a certain role in reducing carbon emissions and protecting the ecological environment.

Measures to improve carbon emission productivity in China: China can improve energy efficiency. China may adopt advanced production technologies, energy saving technologies, and technical standards, thereby promoting

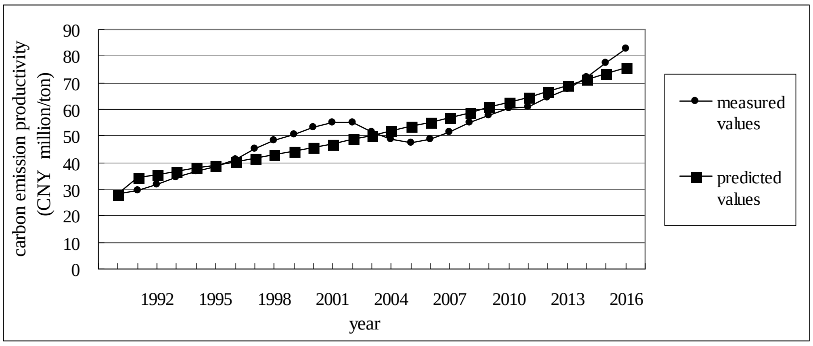

Fig. 1: Comparison between the measured value and predicted value of China's carbon emission productivity between 1990 and 2016.

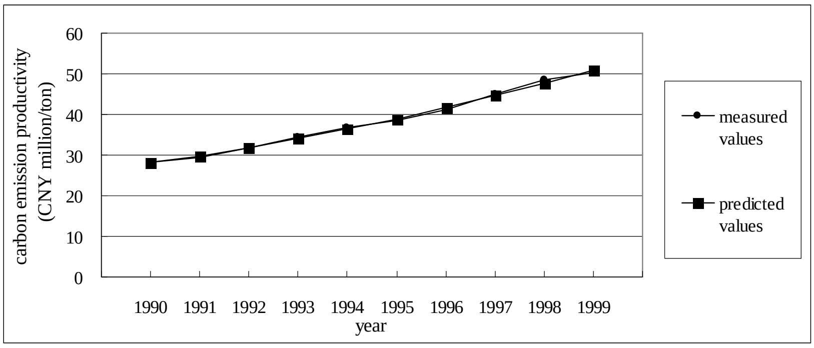

Fig. 2: Comparison between the measured value and predicted value of China's carbon emission productivity in 1990-1999.

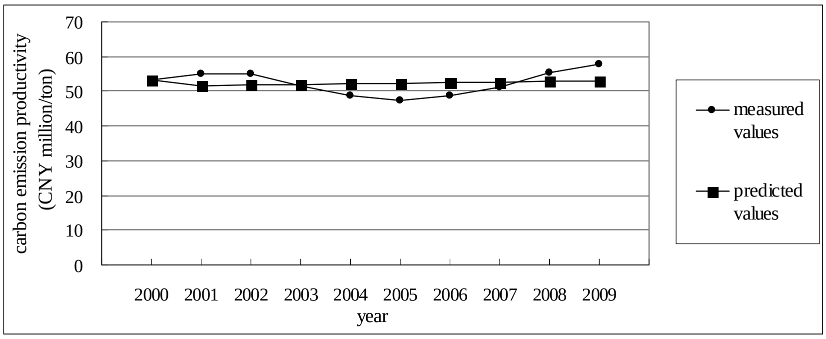

Fig. 3: Comparison between the measured value and predicted value of China's carbon emission productivity in 2000-2009.

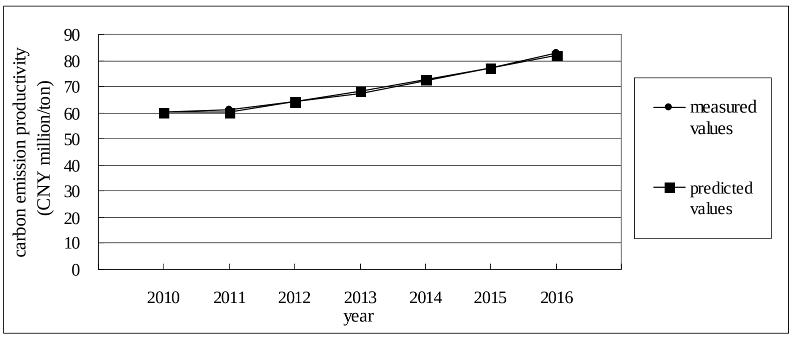

Fig. 4: Comparison between the measured value and predicted value of China's carbon emission productivity in 2010-2016.

Table 8: Test indexes of the GM (1,1) model of each segment.

Year	Mean absolute error	Mean relative error	Correlation degree	variance ratio	Probability of small error	Model accuracy
1990-1999	0.0043	0.0106	0.5464	0.031	1	Qualified
2000-2009	0.0279	0.0537	0.5323	0.493	0.8	Barely Qualified
2010-2016	0.0041	0.0059	0.5698	0.037	1	Good

Table 9: Predicted values of carbon emission productivity between 2014 and 2016.

Year	2014	2015	2016
Carbon emission productivity (CNY million /ton)	87.47	93.04	98.96
Annual growth rate (%)	5.55	6.37	6.36

the improvement of energy efficiency from the technical point of view. China can build a unified national energy market and use market mechanisms to promote energy flow to areas with high energy efficiency. It may formulate reasonable energy prices, ensure energy production, circulation and use, and eliminate energy waste at the same time. China may optimize the industrial layout of high energy consumption projects, and attempt to avoid production projects with high energy consumption in areas with low carbon emission productivity.

China can formulate and implement a micro level carbon budget plan. Since the Kyoto Protocol planners proposed the concept of carbon budget, the budget is mainly formulated and implemented on the levels of global budget and national budget. The carbon budget is mainly based on the mechanism design between countries or regions as a starting point and is a macro level budget. At the micro level, enterprises, families, and all types of social institutions should also improve carbon budget system and implement it in strict accordance with the budget, following their own sustainable development perspective.

China can implement a carbon tax. The country can tax fossil fuel products, such as gasoline, aviation fuel, and natural gas, on the basis of their carbon content, to reduce the consumption of fossil fuels and carbon dioxide emissions.

CONCLUSIONS

The global warming and ecological deterioration caused by carbon emissions have already seriously affected the production and daily life of humanity. In reducing carbon emissions while ensuring the improvement of human living standards and quality of life, the best choice is to increase carbon emission productivity.

On the basis of measuring the carbon emission productivity of China in 1990-2016, this study forecasts the carbon emission productivity level and growth rate in China for a certain future period by using the Grey forecasting model. The results showed that during 1990-2016, China's carbon emission productivity level continued to grow, and the actual GDP brought by unit carbon emissions increased from CNY 28.30 million/ton to CNY 82.87 million/ton, with an average annual growth rate of 4.22%. This result showed that the measures taken by the Chinese government have played a certain role in reducing carbon emissions and protecting the ecological environment. China's carbon emission productivity is expected to continuously increase over the next few years, but its growth rate will slightly decline compared with that in 2010-2016. To achieve the goal of carbon emission reduction, increase carbon emission productivity, and protect human living environment, measures should be taken to improve energy utilization efficiency and formulate and implement micro carbon budget plans and carbon taxes.

This study focuses on the current situation and development trend of carbon emission productivity in China, and studies on carbon tax and carbon budget will be conducted in the future.

ACKNOWLEDGEMENTS

This study was financially supported by the National Planning Office of Philosophy and Social Science of China (No. 12BTJ012).

REFERENCES

Beinhocker, E., Oppenheim, J. and Irons, B. et al. 2008. The Carbon Productivity Challenge: Curbing Climate Change and Sustaining Economic Growth. McKinsey Global Institute, McKinsey and Company, 4-46.

Cha'o-Kuang Chen and Tzu-Li Tien 1996. A new forecasting method for time continuous model of dynamic system. Applied Mathematics and Computation, 80: 225-244.

Che-Chiang Hsu and Chia-Yon Chen 2003. Applications of improved grey prediction model for power demand forecasting. Energy Conversion and Management, 44: 2241-2249.

Chin-Tsai Lin and Shih-Yu Yang 2003. Forecast of the output value of Taiwan's opto-electronics industry using the Grey forecasting model. Technological Forecasting & Social Change, 70: 177-186.

Ernst and Young 2014. Macro-economic impacts of the low carbon transition. European Climate Foundation, Ernst & Young et Associés, 67-75.

He, Jiankun and Su, Mingshan 2009. Carbon productivity analysis to address global climate change. China Soft Science, 226(10): 42-47, 147

Horbach, J. 2008. Determinants of environmental innovation-new evidence from German panel data source. Research Policy, 37(1): 163-173.

Kaya, Y. and Yokobori, K. 1997. Environment, Energy and Economy: Strategies for Sustainability. Tokyo: United Nations University Press, Japan.

Li, Sifeng and Deng, Julong 2000. The range suitable for GM (1,1). Systems Engineering-Theory & Practice, 5(5): 122- 124

Lu, Zhengnan and Yang, Yang 2014. Factor decomposition of carbon productivity in China based on the Laspeyres decomposition method. Journal of Industrial Technological Economics, 8(8): 82-90

Mielnik, O. and Goldemberg, J. 1999. Communication the evolution of the "Carbonization Index" in developing countries. Energy Policy, 27(5): 307-308

Pan, Jiahua and Zhang, Lifeng 2011. Research on the regional variation of carbon productivity in China. China Industrial Economics, 278(5): 47-57

Timmerman, J., Deckmyn, C. and Vandevelde, L. et al. 2014. Low carbon business park manual: A guide for developing and managing energy efficient and low carbon businesses and business parks. Ghent: Ghent University, Belgium.

Won-kyu, Kim 2010. Current issues and implications of Korea's carbon productivity. Available: http://www.businesskorea.co.kr/english/news/industry/436-news-current-issues-and-implications-koreas-carbon-productivity. Accessed 20 May, 2017.

Zhang, Lifeng 2013. Research of total factor carbon productivity and influence factors based on the DEA model. Journal of Industrial Technological Economics, 3(3): 142-149.