A scenario analysis of Chinese Carbon Neutral based on STIRPAT & System Dynamic model

Lei Wen

North China Electric Power University - Baoding Campus

Jie Zhang (✉ 2192218061@ncepu.edu.cn)

North China Electric Power University - Baoding Campus

Zhao Li

North China Electric Power University - Baoding Campus

Research Article

Keywords: STIRPAT model, System Dynamics, Carbon neutral, Situational simulation, Carbon emission

Posted Date: July 26th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-635166/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

A scenario analysis of Chinese Carbon Neutral based on STIRPAT & System Dynamic model

Lei Wen¹ • Jie Zhang² • Zhao Li³

¹ Department of Economics and Management, North China Electric Power University, Baoding 071000, China; Email: wenlei0312@163.com (L.W)

² Department of Economics and Management, North China Electric Power University, Baoding 071000, China; Email: 2192218061@ncepu.edu.cn (J.Z)

³ Department of Economics and Management, North China Electric Power University, Baoding 071000, China; Email: 2192218062@ncepu.edu.cn (Z.L)

*Correspondence: 2192218061@ncepu.edu.cn (J.Z)

Abstract: With the statement of Chinese government on energy saving in 2020 at the United Nations General Assembly, carbon neutral was widely spread as a new concept. As a big country, China has the responsibility and obligation to make its own contribution to global climate change. This paper aims to explore and find effective ways for China to achieve carbon neutrality by 2060. We identify the main factors affecting carbon emissions by STIRPAT model, combined with the scenarios analysis we divide the year 2020 to 2060 into three stages □ year 2020-2030 is Carbon Peak stage, year 2030-2050 is Rapid Emission Reduction stage, year 2050-2060 is Complete Carbon Neutralization stage. At each stage, three development models, high, medium and low level, were established. A total of 27 different scenarios in three stages. A system dynamics model was established to simulate the effects of carbon emission factors and changes in carbon sinks in different scenarios. Finally, 8 paths were found which in line with Chinese current goal of achieving carbon neutrality with treating reach Carbon peak in 2030 as an additional filter condition. Comparing per capita GDP levels in different scenarios, we eventually find that keep economic development at a low level in the first stage, a high level in the second stage and a medium level in the finally stage, the point where net carbon emissions are less than zero for the first time will appear between year 2056-2057. By then, the per capita GDP will reach 144,500 yuan (based on year 2000), nearly four times 2000's. In all, these findings are helpful for policymakers to implement reasonable policies to achieve carbon emission peaking & carbon neutral in China.

Keywords: STIRPAT model □ System Dynamics □ Carbon neutral □ Situational simulation □ Carbon emission

1. Introduction

Climate change, global warming has become an extensive and mature concept. In the past few hundred years, the global temperature has been rising steadily. The trend of global average surface temperature shows that from 1880 to 2012, the temperature rose to 0.89 degrees Celsius. If the atmospheric temperature rises by 2 degrees Celsius, the earth and mankind will face irreversible,

climate catastrophe (Cong et al.,2012). (Gasbarro et al.,2017) studied the relationship between global climate and human activities. In the ten years from 2005 to 2014 alone, global greenhouse gas emissions increased by 19.5%, and the increase in the concentration of greenhouse gases (carbon dioxide, methane, nitrogen oxides, etc.) in the atmosphere is leading to climate change (Du and Xia,2018; Md. Mahmudul Alama et al.,2019). Therefore, in the Paris Agreement signed from 2015 to 2016, a temperature control of two degrees Celsius was set as the future development goal. According to its calculations, the world must reach net zero carbon emissions by 2050, that is, carbon neutrality. Based on the economic growth and social development since implementing economic reform in 1978, China has been a large economic entity second only to the US, furthermore, is also the world's biggest carbon emitter (Ma and Wang,2019) This has attracted a lot of international attention. As a responsible country, at the United Nations General Assembly on September 22, 2020, the Chinese government promised to achieve a carbon peak by 2030 and achieve carbon neutrality by 2060. This is the first time that the Chinese government has proposed such a specific goal at an international conference. This also makes the concept of carbon neutrality spread widely in China. On December 18, 2020, at the China Central Economic Work Conference, carbon neutrality was listed as one of China's eight key tasks in 2021, which is enough to reflect the importance of carbon neutrality.

Undoubtedly, the control of carbon emissions has no time to delay, and accurate prediction of carbon emissions has become a top priority. Against this backdrop, lots of scholars focused on modeling and calculating carbon emissions, and tried to help countries formulate reasonable climate and energy policies. Since 1980s, numerous methods have been established for quantitative analyses on CO₂ emissions. Such as SDA (Wang et al.,2019; Dong et al.,2018; Wu et al.,2019), LMDI (Shi et al.,2019; Quan et al.,2020), LMDI combined with KAYA identity (Ma and Wang,2019; Ma and Ca,2018; Ma et al.,2018), IPAT&STIRPAT (Wen & Shao,2019; Wen & Liu,2016; Lu et al.,2018). Considering the driving factors behind CO₂ emissions in society, economy, and technology aspects, the STIRPAT model is widely used in investigating their contributions to CO₂ emissions. A lot of previous studies only used a single method to analyze the driving factors behind carbon dioxide emissions. For example, Ying et al. (2018) used the STIRPAT model and ridge regression to analyze the current situation and peak prediction of carbon emissions in Guizhou Province, and got a good fitting effect. Zhang and Zhao (2019) applied the STIRPAT model to determine the main influencing factors of China's carbon dioxide. There are also some people combine system dynamics (SD) with the STIRPAT model. For example, Wen and Liu (2015) combined the STIRPAT model with SD model to study the carbon peak time in the Beijing-Tianjin-Hebei region. Liu and Xiao (2018) used the same method to study the Chinese Peak carbon dioxide emissions. Not only the factors behind driving carbon dioxide emissions are obtained, but also the development trends of factors are obtained through system dynamics, which is a big step forward in previous research.

Based on the summary of previous studies on carbon emissions, this article uses the STIRPAT model and system dynamics to explore a feasible way to study Chinese carbon neutrality. This article innovatively combines natural carbon sequestration factors with artificial emission reduction behaviors. It better reflects the overall trend of future development.

This paper uses the STIRPAT model to decompose and study the various factors that affect carbon emissions, and on the basis of the system dynamics model to simulate the trend of the factors affecting carbon emissions, and finally predict China's net carbon emissions based on regression coefficients. This article has made some progress on the previous researches:

No.1 We innovatively put the two targets of carbon peak and carbon neutrality in the same model, which can better reflect the overall trend.

No.2 Integrate natural carbon sequestration and human scientific and technological progress to reduce emissions.

No.3 The simulation with a time span of 40 years is divided into 3 stages, and the goals and tasks of each stage are proposed respectively. Based on this, all possibilities are exhausted to ensure the rationality of the forecast.

No.4 Based on the situational simulation of system dynamics, we have found a way to achieve carbon peak and carbon neutrality.

In short, these results can give the Chinese government a certain reference value when formulating future development policies.

The rest of the paper is organized as follows: Section 2 presents the current situation of CO₂ emissions and carbon sink in China. Section 3 provides the data and methodology. Section 4 shows the results and discussion.

2.The current situation of CO₂ emissions and carbon sink in China.

The changes in carbon sink from different projects, over the period 2000–2019 are presented in Fig. 1. Note that the calculation method will be showed in next section. It can be found that Chinese total carbon sinks grew slowly during the 13 years from 2000 to 2012, and changed slowly after a small increase in carbon sinks in 2013. This is caused by the delay of Chinese statistics. On the whole, Chinese overall natural carbon sink has remained stable over the past 20 years, with a slight increase year by year, far from reaching the upper limit of natural carbon sink. In addition, it is worth noting that although the forest system is the largest carbon sink storage system in the terrestrial ecosystem, it is not the largest carbon sink growth point in the ecosystem. The huge carbon sink storage of the forest comes from long-term reserves, but It grows slowly. Farm system has become the largest contributor to the annual growth in the amount of carbon sinks, perhaps because most of the crop growth cycle is less than one year, one year all generated carbon sinks are credited for the growth in carbon sinks. The ranking of the contribution to the growth of carbon sinks in descending order is: farmland (including crops), grassland, forest, wetland, orchard.

Fig.1. carbon sink from different types in 2000–2019.

The changes in Chinese carbon emissions from year 2000 to 2019 are presented in Fig. 2. To

reflect the overall trend in China carbon emissions, This paper calculates the carbon emissions from fossil fuel use, livestock farming and rice fields(equivalent carbon emissions due to the greenhouse effect caused by methane emissions). As shown in the figure, among China's total carbon emissions, carbon dioxide emissions from fossil fuel use account for nearly 90% of the total carbon emissions, livestock equivalent carbon emissions account for nearly 7%, and rice field carbon emissions account for 3%. From 2000 to 2019, the overall trend of my country's carbon emissions has gradually increased. Especially from 2002 to 2013, my country's carbon emissions have increased rapidly, from less than 4 billion tons in 2002 to more than 10 billion tons in 2013, with an average annual growth rate of nearly 10%. Since 2013, carbon emissions have declined slightly due to the reduction in coal use, and the total carbon emissions have rebounded slightly since 2017.

Fig.2. CO2 emissions from different types in 2000–2019.

3. Methodology

3.1 STIRPAT model

IPAT is a quantitative relationship model that expresses the impact of human activities on the environment. This method was first proposed by Ehrlich and Holden. The IPAT method believes that the increase in population, the improvement of material living standards, and the scientific and technological progress of resource development and utilization are the root causes of increasing pressure on resources and the environment; With the limited supply of resources and environmental capacity to cope with the infinite pursuit of material desires by the expanding population, the socio-economic development is bound to be unsustainable. The impact of human activities on the environment is the result of population growth, economic growth, and technological progress. The population size, wealth and technological level can be used to measure the environmental pressure of economic development. Achieving sustainable social and economic development requires the coordinated development of population, resources, environment, and economy. If there is an imbalance in quantity, then resource and environmental issues will become a bottleneck for economic growth. Through in-depth analysis of the reasons for the deterioration of environmental quality, Ehrlich et. expresses the pressure of human activities on the environment as the product of the extent of population, wealth and technological progress□

$$I = P \times A \times T \quad (7)$$

Where I represents the environmental pressure; including resources, energy consumption and waste discharge et al.; P is the number of population reflecting the change of population size; A is the extent of wealth, usually expressed by per capita GDP; T is the degree of technological progress,

usually expressed in terms of energy consumption or pollutant emissions per unit of GDP. Since the IPAT model was proposed, it has been widely used and some extended models have been developed. Waggoner et al. decomposed T into energy consumption per unit GDP (C) and the impact of unit consumption on the environment (T), and the IPAT model was extended to the IPACT model; In recent years, researchers have used the IPAT method to explore the contribution of driving forces such as population, wealth, and technology to land use, resource consumption, pollutant emissions, etc., and analyze the sources and changes of environmental pressures. The IPAT framework is simple and the method is simple, but there are also insurmountable problems in the application process. For example IPAT simplifies the relationship between economic development and resources and environmental pressures. In fact, resource development, environmental pollution, and the level of social and economic development are often not a simple linear relationship. In order to overcome the limitation of the same proportional linear relationship between environmental impact and each driving force, Dietz et al. proposed the random regression impact model STIRPAT□

$$I = aP^a A^b T^c z \quad (8)$$

Taking the natural logarithm on both sides at the same time, the equation can be transformed into:

$$\ln I = \ln a + a \ln P + b \ln A + c \ln T + \ln z \quad (9)$$

Among them, I, P, A, and T have the same meaning as mentioned before; a, b, and c represent the elastic coefficients of I, P, A, and T respectively, and z represents the residual term.

Based on this, we propose a decomposition model of Chinese carbon emissions influencing factors□

$$\ln I = \ln a + a \ln P + b \ln A + c \ln IS + d \ln ES + f \ln EI + \ln z \quad (10)$$

In the formula, I represents carbon dioxide emissions, P represents population, A represents per capita GDP, IS represents industrial structure (the proportion of tertiary industry), ES represents energy structure (the proportion of coal use in total energy), EI stands for energy intensity (the ratio of total energy consumption to total GDP, indicating the level of technological development.).

Based on the above analysis, the carbon dioxide emission prediction model can be written as□

$$I = e^{(\ln a + a \ln P + b \ln A + c \ln IS + d \ln ES + f \ln EI + \ln z)} \quad (11)$$

3.2 Data processing: The collection of data is a huge task. We have checked and collected the total energy consumption, the total number of livestock in the livestock industry, the area of rice fields, and the specific data of natural carbon sink factors in Chinese statistical yearbooks from 2000 to 2019. We use the stock volume method (Shi et al.,2014) to calculate the annual total forest carbon sink of the forest, compare the carbon sink amount of the next year, and use the difference as the forest carbon sink of the year.

$$CF = (S_{ij} \times C_{ij}) + \alpha(S_{ij} \times C_{ij}) + \beta(S_{ij} \times C_{ij}) \quad (1)$$

$$C_{ij} = V_{ij} \times \sigma \times \rho \times \gamma \quad (2)$$

Where CF represents the total carbon sink; S_{ij} represents the area of type j forest in area i; C_{ij} represents the carbon density of type j forest biomass in area i; V_{ij} represents stock volume per unit area of type j forest in area i; α Indicates the carbon conversion coefficient of understory plants; β Indicates the carbon conversion coefficient of forest land; σ, ρ & γ represent biomass expansion coefficient, volume coefficient and carbon content, respectively, volume factor and carbon content. According to the crop primary net productivity method (Wu and Yang,2020), the carbon sink reserves of farming are calculated and included in the farmland carbon sink.

$$C_t = \sum_1^i C_d = \sum_1^i C_f \times D_w = \sum_1^i C_f \times \frac{Y_w}{H_i} \quad (3)$$

Where C_t represents the total carbon absorption of the entire farmland ecosystem ; i represents the type of crop C_d represents the carbon uptake of the i -th crop during the whole growth period C_f represents the carbon absorption rate of the i -th crop D_w represents the production volume of category i crops Y_w represents the economic output of category i crops H_i represents the economic coefficient of the i -th crop. The crop economic coefficient and carbon absorption rate are shown in Table 1.

Table 1
Crop economic coefficient, carbon absorption rate.

Types of crops	Economic coefficient	Carbon absorption rate
Corn	0.400	0.471
Sorghum	0.350	0.450
Rice	0.450	0.414
Wheat	0.400	0.485
Millet	0.400	0.450
Tubers	0.700	0.423
Soybeans	0.350	0.450
Other food crops	0.400	0.450
beet	0.700	0.407
tobacco	0.550	0.450
cotton	0.100	0.450
vegetables	0.300	0.450
rape	0.250	0.450
Chinese cabbage	0.738	0.450
sunflower	0.300	0.450
peanut	0.430	0.450
sugar cane	0.685	0.450

The carbon sequestration of farmland, orchard land, grassland, and wetland is calculated using the method of multiplying the area by the carbon sequestration coefficient (Yu et al.,2016).

$$C = \sum_i S_i \times T_i \quad (4)$$

Where C represents the total carbon sink S_i represents the area of project i T_i represents the carbon fixation coefficient of project i .

Table 2
Carbon fixation coefficient table of each project.

Accounting project	Accounting Method	Carbon sequestration coefficient (t/ha year)
Forest	Stock volume method	--
Farmland	Crops: Primary Net Productivity Method Land: Carbon Fixation Coefficient Method	7.974
Orchard	Carbon Fixation Coefficient Method	7.262
Grassland		1.3
Wetlands		3.95

Since there is no direct carbon source data to query, we use the (IPCC, 2006) Greenhouse Gas Emission Guidelines to calculate Chinese fossil fuel carbon dioxide emissions:

$$CO_2 = \sum_i E C_i \times E_i = \sum_i \frac{O_i \times LCV_i \times CC_i}{CF_i} \times \frac{44}{12} \times E_i \quad (5)$$

Where i represents different types of fossil fuels ($i = 1, 2, 3, 4, 5, 6, 7$); E_i represents the consumption of type fuel i ; EC_i represents the carbon emission coefficient of the i -th fuel; O_i represents oxidation rate of fuel type i ; LCV_i represents lower calorific value of fuel type i ; CC_i is carbon content of fuel type i ; CF_i represents conversion factor of fuel type i .

Bio-equivalent carbon dioxide emissions:

$$CO_2 = GWP \times \sum_i CH_4 = GWP \times S \times V + GWP \times \sum_j Q_j \times T_j \quad (6)$$

Where $i = (1, 2)$, $i = 1$ represents methane emissions from rice fields; $i = 2$ represents methane emissions from large livestock; S represents the area of rice fields; V represents the methane emission rate from paddy fields; j represents different types of livestock; Q_j represents the number of livestock type j ; T_j represents the type j livestock methane emission factor; GWP is the abbreviation of Global Warming Potential ($CO_2 = 1, CH_4 = 25$) (Du and Xia, 2018).

Table 3

Conversion factor table corresponding to various types of fossil fuels.

Energy resource	Natural gas	Fuel oil	Coal	Coke	Gasoline	Kerosene	Diesel
Conversion factor (tce/t Or kgce/m ³)	1.33	1.4286	0.7143	0.9714	1.4714	1.4714	1.1571
Oxidation rate	99%	98%	94%	93%	98%	98%	98%
LCV (kJ/kg or kJ/ m ³)	38931	41816	2908	28435	43070	43070	42652
Carbon Content (tC/TJ)	15.3	21.1	26.37	29.5	18.9	19.5	20.2
Emissions Coefficient (tCO ₂ /tce)	1.6275	2.2193	2.6604	2.9446	1.9879	2.051	2.1247

Table 4

Biomethane emission factor .

Animal and plant species	Emission factor	Animal and plant species	Emission factor	Animal and plant species	Emission factor
Cattle	59	Mule	10.9	Sheep	5.15
Horse	19.64	Camel	47.92	Poultry	0.01
Donkey	10.9	Pig	6	Rice	100.128

3.3system dynamics (SD)

System Dynamics (SD) was originally derived from the work of Jay W. Forrester and his colleagues at the MIT Sloan School of Management in the 1960s. The original system dynamics thought was formed when they applied the concept of feedback control theory to study industrial systems. Forrester completed the book "Industrial Dynamics" and used Dynamo to implement the model. Xiao et al. (2016) studied Chinese 2020 carbon intensity target based on system dynamics using scenario analysis. Xiao and Liu (2018) used the same method to study China's carbon peak in 2030. Because system dynamics has incomparable advantages in complex system simulation and prediction, this article uses a system dynamics model to simulate the comprehensive development trend of each variable in the STIRPAT model, and calculates the carbon dioxide emission equivalent in each situation based on the prediction model.

3.3.1 SD model of carbon neutral

Fig. 3. Flow diagram of SD model.

3.4 Scenario settings.

In order to make the setting of the situation more real and reliable, this article uses the situation analysis method to combine with historical data, and sets the parameters of each situation according to the latest government guidance documents.

This article divides the period from 2020 to 2060 into three phases. From 2020 to 2030 is the carbon peak phase, from 2030 to 2050 is the rapid emission reduction phase, and from 2050 to 2060 is the carbon neutral phase.

According to the characteristics of each stage, three development modes of high-speed, medium-speed and low-speed are set up. The growth rate of each indicator of each mode is shown in Table 7. A total of 27 different development models, as shown in Fig. 8.

Judging from historical data, Chinese GDP has been maintaining rapid development, but in recent years, with the increase in volume and changes in economic structure, the growth rate of GDP has slowed down.

According to the "China in 2030" published by the World Bank and the Development Research Center of the State Council, the prediction of China's future economy, we set the GDP growth rate for the period from 2020 to 2030 between 5% and 5.9%, and the high and low scenarios fluctuate 0.5% on the basis of 5%. The growth rates of the tertiary industries are determined according to the proportion of the total tertiary industries, the total population will increase further under the conditions of the opening of the two-child policy, and the cost of clean energy will gradually decrease, leading to an increase in the use of clean energy. However, due to the insignificant decline in the use of coal at the technical level, the dependence on oil is still significant. The excessive use of natural gas as a clean energy product will rise sharply, the area of forests, grasslands, wetlands, etc. will maintain a small increase, and the area of farmland will not change significantly. During the period from 2030 to 2050, due to the huge economic aggregate, the growth rate of the first, second and third industries will decline significantly, and the country will enter the threshold of a moderately developed country. According to the economic growth data of moderately developed countries, we set the economic growth rate to 3%, and determine the growth rates of the tertiary industries according to the total proportion of the tertiary industries. With the demographic dividend period of the 1960s and 1970s, people born in the demographic dividend period gradually entered the 60-year-old threshold, the aging of the population further aggravates the population will decline slightly, the cost of clean energy has been further reduced due to the development of technology. The use of clean energy continues to maintain rapid growth, and the dependence on energy such as coal and petroleum has dropped significantly. The use of natural gas continues to grow, but due to the huge volume, the growth rate has decreased significantly. The changes in natural carbon sink factors at this stage are still increasing slowly. During the carbon neutral period from 2050 to 2060, Chinese economy is huge, and the focus of development will continue to shift from economic construction to environmental protection, and economic growth will further slowdown. The aging of the population has eased, the number of people has rebounded slightly, clean energy has become the main force in energy use, the use of energy has continued to grow, the use of coal, oil and other energy continues to decline, the use of natural gas has flattened, and the natural carbon sink has increased significantly. The growth rate corresponding to each stage is shown in Table 5.

Table 5

Table of growth rates corresponding to each stage.

	2020-2030			2030-2050			2050-2060		
	Low	Medium	High	Low	Medium	High	Low	Medium	High
Primary industry	2.0%	3.0%	4.0%	1.5%	2.0%	2.5%	0.5%	1.0%	1.5%

growth rate									
Secondary industry growth rate	4.5%	5.0%	5.5%	1.5%	2.0%	2.5%	0.5%	1.0%	1.5%
Tertiary industry growth rate	6.5%	7.0%	7.5%	3.5%	4.0%	4.5%	2.5%	3.0%	3.5%
Birth rate	0.9%	1.2%	1.5%	0.6%	0.9%	1.2%	0.4%	0.7%	1.0%
Population mortality	0.7%	0.7%	0.7%	1.0%	1.0%	1.0%	0.65%	0.65%	0.65%
Natural population growth rate	0.2%	0.5%	0.8%	-0.4%	-0.1%	0.2%	-0.25%	0.05%	0.35%
Clean energy growth rate	8.0%	10.0%	12.0%	6.0%	8.0%	10.0%	3.0%	4.0%	5.0%
Coal use growth rate	-1.5%	0	1.5%	-5.5%	-5.0%	-4.5%	-1.5%	-1.0%	-0.5%
Oil use growth rate	2.7%	3.0%	3.3%	-1.3%	-1.0%	-0.7%	-2.1%	-1.8%	-1.5%
Natural gas use growth rate	9.0%	12.0%	15.0%	2.0%	5.0%	8.0%	-2.0%	1.0%	3.0%
Forest area growth rate	1.3%	1.0%	0.7%	1.8%	1.5%	1.2%	1.7%	2.0%	2.3%
Farmland area growth rate	0	0	0	0	0	0	0	0	0
Orchard area growth rate	1.0%	0.5%	0	1.5%	1.0%	0.5%	2.5%	2.0%	1.5%
Wetland area growth rate	2.3%	2.0%	1.7%	2.3%	2.0%	1.7%	4.3%	4.0%	3.7%
Grassland area growth rate	1.3%	1.0%	0.7%	1.3%	1.0%	0.7%	2.0%	2.0%	1.7%

4 Results and discussions

In this paper, total carbon emissions are used as dependent variables, and population (POP), GDP per capita (A), industrial structure (IS) (the proportion of tertiary industry), energy structure (ES) (the proportion of coal use), and energy intensity (EI) as the independent variable. In fact, the respective variables are not independent of each other but there is serious multicollinearity. The correlation of all variables is shown in the Table 6.

Table 6

Correlation coefficient table.

Correlation						
	Carbon emission	Population	GDP per capita	Energy intensity	Energy structure	Industrial structure
Carbon emission	1	0.974	0.983	-0.778	-0.586	0.887
Population	0.974	1	0.996	-0.892	-0.734	0.950
GDP per capita	0.983	0.996	1	-0.878	-0.696	0.933
Energy intensity	-0.778	-0.892	-0.878	1	0.929	-0.887
Energy structure	-0.586	0.734	-0.696	0.929	1	-0.785
Industrial structure	0.887	0.950	0.933	-0.887	-0.785	1

Note: All the correlation coefficients are significant at 5%.

Owing to the reason of possible interaction between variates, the variates' marginal impact cannot be reflected by regression coefficients obtained through OLS. Therefore, this paper uses the ridge regression method to estimate the coefficients in the STIRPAT model. The ridge trace diagram and the RSQ vs. k diagram are shown in Fig. 4 and Fig. 5.

Fig. 4. The ridge trace diagram.

Fig. 5. the RSQ vs. k diagram.

eventually, when $k=0.26$, the ridge trace graph tends to be flat, the fitted ridge regression equation is as follows:

$$\begin{aligned} \ln C = & -35.4948 + 4.28679 \times \ln POP + 0.286558 \times \ln A - 0.130207 \times \ln EI + 0.5832 \\ & \times \ln ES + 1.73537 \times \ln IS \end{aligned} \quad (12)$$

According to the system dynamics simulation, the net carbon emission diagram of each situation is shown in [Fig. 6](#).

Fig. 6. Net carbon emissions in each situation.

According to the simulation of the 27 development models one by one, we have obtained the future development of the net carbon emissions of the 27 different models. In the case of the established 27 models, the net carbon emissions of all models will show varying degrees of growth from 2020 to 2030, and an extreme point will appear around 2030, which means that all models can

achieve carbon emissions around 2030. In the 20 years from 2030 to 2050, the net carbon emissions in all scenarios will decline rapidly as planned. In the period from 2050 to 2060, the decline in net carbon emissions in some scenarios tends to be flat. In the 20 years from 2030 to 2050, the net carbon emissions in all scenarios will decline rapidly as planned. In the period from 2050 to 2060, the decline in net carbon emissions in some scenarios tends to be flat. The total carbon emissions chart for all scenarios are shown in Fig. 7.

Fig. 7. Total carbon emissions in each situation.

Among the 17 scenarios that have achieved carbon neutrality by 2060, those with a carbon peak of less than 15 billion tons in 2030 have 111,112,113,121,122,123,131,132 eight scenarios. This means that these eight scenarios will not only peak carbon emissions in 2030, but also control the total amount within 15 billion tons, and achieve carbon neutrality by 2060. Among them, the per capita GDP corresponding to scenario 132 will reach 144,500 yuan by 2060 (based on 2000), which is nearly four times that of 38,000 in 2020, which is the highest among all scenarios that meet the above three conditions at the same time. The schematic results of GDP per capita in all scenarios are shown in Fig. 8.

		2020-2030				
		Low	Medium	High		
2030-2050	Low	111	211	311	Low	2050-2060
		112	212	312	Medium	
		113	213	313	High	
	Medium	121	221	321	Low	2050-2060
		122	222	322	Medium	
		123	223	323	High	
	High	131	231	331	Low	2050-2060
		132	232	332	Medium	
		133	233	333	High	

Fig. 8. Schematic diagram of GDP per capita in each situation.

Note: For example, Scenario 132 means to maintain a low-speed economic development model in the period from 2020 to 2030, maintain a high-speed economic development model in the period from 2030 to 2050, and adopt a medium-speed economic development model in the period from 2050 to 2060.

Yellow shading indicates that carbon neutrality can be achieved by 2060. Blue shading means that on the basis of achieving carbon neutrality by 2060, the peak carbon emission at the same time is controlled below 15 billion tons. Red shading represents the highest GDP per capita among all blue background scenarios by 2060. Those without a background will not be able to achieve the carbon neutral situation before 2060. The background color of the table represents the value of GDP per capita, the lighter the color, the greater the value.

5. Discussion

The situation in the Fig. 8 is closer to the lower right corner, the higher the GDP per-capita, we found that the scenarios that can achieve the carbon neutral goal by 2060 are mostly concentrated in the upper left part of the table, and the scenarios where the peak carbon emissions are controlled within 15 billion tons are all concentrated in the first column. On the whole, in order to achieve the goal of carbon neutrality, China must appropriately reduce its economic growth rate and cannot blindly pursue a high-speed economic development model. In stages, between 2020 and 2030, maintaining a slow economic growth, vigorously developing new technologies, reducing the cost of clean energy, and gradually reducing dependence on fossil energy such as coal, and actively adjusting the energy structure is a better model. From 2030 to 2050, because of the control of carbon emissions in the previous stage, the pressure of carbon emission reduction at the beginning of this stage is less than that of other situations, therefore more energy can be invested in the construction and development of the economy, and the people's life and well-being will be greatly improved at this stage. Between 2050-2060, the final stage of carbon neutrality, with the industrial structure in the first two stages, the adjustment of the energy structure, and the increase in natural carbon sinks such as forests, grasslands, wetlands, etc., net carbon emissions will continue to decrease and will appear to be less than zero between 2055-2056.

Declarations

Ethics approval and consent to participate

Not applicable

Consent for publication

Not applicable

Availability of data and materials

The authors declare that data supporting the findings of this study are available within the article.

Competing interests

The authors declare no conflict of interest.

Funding

This manuscript unfunded support

Authors' contributions

All authors contributed to the study conception and design. Material preparation, Data collection and analysis were carried out by Lei Wen , Jie Zhang and Zhao Li. The first draft of the manuscript was written by Jie Zhang and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

References:

- Alam M M , Murad M W , Normanc A H M , et al. Relationships among carbon emissions, economic growth, energy consumption and population growth: Testing Environmental Kuznets Curve hypothesis for Brazil, China, India and Indonesia[J]. Ecological Indicators, 2016, 70(nov.):466-479.
- China in 2030: Building a modern, harmonious and creative society.
- Cong Aili,Zheng Chongwei,Tian Yanyan,Zhou Dandan.Study on the overall change trend of global temperature in the past 100 years[J].China Science and Technology Information,2012(22):38.
- Dong, F., et al., Drivers of carbon emission intensity change in China. Resources, Conservation and Recycling, 2018. 129: p. 187-201.
- Du, W.C. and X.H. Xia, How does urbanization affect GHG emissions? A cross-country panel threshold data analysis. Applied Energy, 2018. 229: p. 872-883.
- Fang, W., et al., Accessing on the sustainability of urban ecological-economic systems by means of a coupled energy and system dynamics model: A case study of Beijing. Energy Policy, 2017. 100: p. 326-337.
- Gasbarro F, Iraldo F, Daddi T. 2017.The drivers of multinational enterprises' climate change strategies: A quantitative study on climate-related risks and opportunities[J]. Journal of Cleaner

Production, 160: 8-26.

IPCC, 2006. IPCC Guidelines for National Greenhouse Gas Inventories, National Greenhouse Gas Inventories Programme. IGES, Japan.

Liu, Y. and L. Wen, The Peak Value of Carbon Emissions in the Beijing-Tianjin-Hebei Region Based on the STIRPAT Model and Scenario Design. *Polish Journal of Environmental Studies*, 2016. 25(2): p. 823-834.

Lu Ying, Li Xudong, Yang Zhengye. Current status and peak forecast of energy carbon emissions in Guizhou Province[J]. *Environmental Science and Technology*, 2018, 41(11): 173-180.

Ma, M. and W. Cai, What drives the carbon mitigation in Chinese commercial building sector? Evidence from decomposing an extended Kaya identity. *Science of The Total Environment*, 2018. 634: p. 884-899.

Ma, M., W. Cai and W. Cai, Carbon abatement in China's commercial building sector: A bottom-up measurement model based on Kaya-LMDI methods. *Energy*, 2018. 165: p. 350-368.

Ma, X., et al., Carbon emissions from energy consumption in China: Its measurement and driving factors. *Science of The Total Environment*, 2019. 648: p. 1411-1420.

Quan, C., et al., Analysis on the influencing factors of carbon emission in China's logistics industry based on LMDI method. *Science of The Total Environment*, 2020. 734: p. 138473.

Shi Xiaoliang, Zhang Ying, Han Zhengwei. A review of forest carbon sink measurement methods-based on the choice of Beijing[J]. *Forestry Economics*, 2014, 36(11): 44-49.

Shi, Y., et al., Uncovering the national and regional household carbon emissions in China using temporal and spatial decomposition analysis models. *Journal of Cleaner Production*, 2019. 232: p. 966-979.

Shi, Y., et al., Uncovering the national and regional household carbon emissions in China using temporal and spatial decomposition analysis models. *Journal of Cleaner Production*, 2019. 232: p. 966-979.

Sun Xiao, Jiang Xueling, Yang Jianchao, Chen Kang, Zhang Zhantian, Zhang Guanghe, Cui Yuming, Jiang Lihua, Cui Rongzong. The effects of different fertilization modes on the physical and chemical properties and yield of vegetable soil[J]. *Jiangsu Agricultural Sciences*, 2020, 48 (07):169-173.

Wang, Z., et al., Regional difference and drivers in China's carbon emissions embodied in internal trade. *Energy Economics*, 2019. 83: p. 217-228.

Wen, L. and H. Shao, Analysis of influencing factors of the carbon dioxide emissions in Chinese commercial department based on the STIRPAT model and ridge regression. *Environmental Science and Pollution Research*, 2019. 26(26): p. 27138-27147.

Wu Jiabin, Yang Hongjuan. A review of research on the methods of agricultural net carbon sink calculation[J]. *Agricultural Economics*, 2020(10): 29-31.

Wu, F., et al., Multi-province comparison and typology of Chinese CO₂ emission: A spatial-temporal decomposition approach. *Energy*, 2020. 190: p. 116312.

Xiao, B., D. Niu and X. Guo, Can China achieve its 2020 carbon intensity target? A scenario analysis based on system dynamics approach. *Ecological Indicators*, 2016. 71: p. 99-112.

Yang Rongzhong, Zhou Hui, Lei Jingchao, Duan Weixing, Tang Shiyun, Li Wenjiao, Yang Cuifang, Gao Yijing, Zhou Shan. Research on the Harvest Index of Different Sugarcane Varieties[J]. *China Sugar*, 2019, 41(01): 8-12 .

Yu Weiyong, Qi Yanbin, Ming Hui, Ren Dan, Deng Xin, Fu Li. Provincial differences and

451 influencing factors of carbon sinks and carbon sources in Chinese agricultural system[J].
452 Western Forestry Science, 2016, 45(05):1-7.
453 Zhang Zheyu. Research on Accounting Method of Greenhouse Gas Emissions of Pig Breeding
454 Enterprises[D]. Beijing University of Architecture and Architecture, 2018.