Carbon Emission Scenario Projections Based on STIRPAT Modeling: Evidence from Anhui

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Abstract. As a matter of fact, carbon emission is a hot topic in contemporary society. This paper focuses on the carbon emission problem in Anhui Province, and adopts the IPCC method to measure the industrial carbon emission and total carbon emission in each region of Anhui Province, and analyses the decoupling of GDP and carbon emission in each region of the province from 2011 to 2020 based on the Tapio decoupling model. In addition, this study constructs a prediction model for the trend of carbon emission in the industrial sector of Anhui Province by using the STIRPAT model, and sets up three different scenarios for the indicators of the size of the industrial economy, the industrial output value per capita, the energy structure, the energy intensity, and the intensity of the industrial sector's carbon emission in Anhui, including the energy saving, the baseline, and the aggressive scenarios. According to the analysis, weakly decoupled relationship between GDP and carbon emissions in various regions of Anhui Province. In addition, the peak carbon emissions are 459.27 million tons, 493.25 million tons, and 562.48 million tons in 2030, 2035, and 2040 in the three different scenarios, namely, energy conservation, baseline, and aggressive scenarios, respectively.

Keywords: STIRPAT model, Tapio model, carbon footprint, Anhui province.

1. Introduction

Early in the twentieth century, scientists realized that combustion emissions from industrial activities could have an impact on atmospheric composition, but it was not until the 1960s that the first formal global CO_2 measurement network was established. However, it was not until the 1960s that the first formal global network of CO_2 measurements in human history was established; Keeling began measuring CO_2 at Mathers Peak, Hawaii, in 1958, and established a long-term observing system that revealed trends in atmospheric CO_2 concentrations that were increasing from year to year [1]. With the passage of time, the development of technology, and the development of knowledge in a variety of related disciplines, climate modeling has evolved tremendously, and the development of climate models has allowed scientists to better understand the relationship between anthropogenic carbon dioxide and climate change. Charney et al., in a 1979 study, made the first imperceptible assessment of the effects of carbon dioxide on global climate assessment [2]. In 1988, the Intergovernmental Panel on Climate Change (IPCC) was established. The IPCC reports provide the international community with authoritative information on carbon dioxide emissions and global warming, and they describe The global carbon budget, including the sources, aggregation and distribution of CO_2 emissions, is very helpful in understanding the rationale for the role of CO_2 emissions in climate change [3]. As time progresses, remote sensing and other technologies become more accurate and developed, scientists have been able to more accurately detect global carbon dioxide emissions, and Pierre Friedlingstein et al. have shown that carbon dioxide from human-induced fossil fuel combustion is the main source of climate-affecting carbon dioxide gases [4].

The IPCC released its special report "1.5 Degrees Celsius Global Warming" in 2018, which shows that Anthropogenic carbon emissions are one of the main factors triggering the rise in global temperatures, and at the same time, global warming has triggered a series of climate change phenomena [5]. In 2020, Le et al. reveal short-term reductions in carbon emissions from embargoes during the COVID-19 pandemic, highlighting the strong link between carbon emissions and climate, and they point out that the short window of emission reductions during the epidemic revealed the

mitigating effect of emission reductions on global warming. The importance of structural change was also emphasized [6]. The study by Pierre Friedlingstein et al. reveals the complex ways in which carbon-containing elements, such as carbon dioxide, interact with the atmospheric carbon cycle as a result of human activities, and proposes the concept of a global carbon budget, and states that emission reductions are the key to achieving a carbon balance, expressing the urgency of limiting carbon emissions [7]. Hansen et al. first quantified the impact of CO_2 emissions on the climate in 1981, while introducing the concept of the greenhouse effect [8]. Additionally, in one of his 2013 studies, he emphasized the importance of reducing carbon emissions in order to protect the younger generation as well as the natural environment from potential climate change threats. This study argues that the necessary emissions reductions are necessary to maintain sustainable climate conditions [8].

In response to global warming, countries around the world have introduced various policies to reduce emissions of carbon-containing substances that affect climate change, and China, as the largest developing country, has responded positively to the international community's call for emissions reduction by proposing a carbon-neutral and carbon-peak target. Carbon peak, that is, the gradual increase in carbon emissions to its historical peak into a stable platform period, from the inflection point to gradually reduce the process; carbon neutral is the greenhouse gases through technology, biological carbon sequestration and other means to achieve "net-zero emissions". In order to reduce carbon dioxide emissions, many institutions at home and abroad have conducted a lot of research on carbon emissions and related issues. So far, the main methods of carbon emission prediction include IPAT model, STIRPAT model, Kaya constant equation, LEAP model, BP neural network, Logistic model, LMDI decomposition method, etc. Zhang et al. used the STIRPAT model to study the carbon emission influencing factors in the urbanization process of Anhui Province back in 2014 [9]. Li et al. analyzed the interaction between the change of urban area and industrial composition and carbon emissions, and proposed that the expansion of urban size and the upgrading of economic scale will increase the emission of carbon dioxide and carbon-containing substances [10]. In view of the interaction and connection between carbon emission and economic growth, Tapio established a Tapio decoupling model linking carbon emission and GDP [11].

Anhui Province is an important part of the Yangtze River Delta economic belt, a key position in national economic development, and a neighbour of several important leading economic development regions. Clarifying the interaction between CO_2 emissions and GDP in Anhui Province and predicting the future trend of CO_2 emissions will provide an important reference template for emission reduction in other regions in East China and the Yangtze River Delta. In this paper, the IPCC method is used to calculate the CO_2 emissions of each prefecture-level city in Anhui Province, and then the Tapio decoupling model is used to calculate the decoupling of CO_2 emissions and GDP in 16 prefecture-level cities in Anhui Province, and the STIRPAT model is used to predict the carbon emissions.

2. Data and Method

2.1. Data

In order to ensure the accuracy of the data obtained in this paper, and because most of the data used in this paper come from the consumption side, the calculation will be based on the carbon dioxide emissions accounting of the consumption side, and calculate the carbon dioxide emissions generated by the products and services needed to support economic development [12]. This study will use the IPCC industry carbon emission calculation method at the consumer

$$\text{Cit}=\sum_j E_{ijt} \times a_j \tag{1}$$

In this equation, Cit is the total carbon emissions in year t in region i, and E_{ijt} is the discounted CO_2 coefficient for energy source j in year t in region i (seen from Table 1). For the estimation of industrial carbon emissions in Anhui Province, this study will use the carbon emission model for the

industrial sector in Anhui Province obtained by combining the bottom-up pathway approach provided by the IPCC with the actual situation in Anhui Province in 2022, as shown as:

$$CO_2 = \sum_{i=1}^{6} E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \quad (2)$$

Here, CO_2 is estimated CO_2 emissions, Ei is the quantity of the ith energy source used over a fixed time horizon, NCV_i is the average low level heat generation of the ith energy source, CEF_i is the carbon emission factor of the ith energy source, COF_i is the carbon oxidation factor of the ith energy source, and 44/12 is the ratio of the relative molecular mass of the carbon dioxide molecule to the carbon atom. Anhui Province has not yet officially released its annual carbon emissions data, so the carbon emissions data used in this article are based on the real data published by the Anhui Provincial Bureau of Statistics and the National Bureau of Statistics, such as the "Anhui Provincial Statistical Yearbook" and the "China Urban Statistical Yearbook", and then combined with the energy data and the national economic data, to estimate carbon dioxide emissions in Anhui over a 10-year period (Fig.1). In order to test the usability of the results obtained from the calculations, the results were subjected to an error analysis with the data of Wang [13], and the error is within the controllable range, which proves that the method is acceptable and the calculation results can be used, and the data will be used in future calculations. The reference for GDP data for Anhui Province is the Anhui Statistical Yearbook published by the Anhui Bureau of Statistics in 2022. Since the 2023 Anhui Statistical Yearbook has not yet been released, the GDP data used in this article only goes up to 2021.

Table 1. Energy conversion factors

renewable energy	Average low level heat genera-tion kJ/kg	Discount factor for standard coal kgce/kg	Carbon content per unit calorific value tC/tJ	carbon oxidation rate	CO_2 discount factor $kgCO_2/kg$	Standard coal to carbon dioxide factor $kgCO_2/kgce$
raw coal	20908	0.7143	26.37	0.94	1.9003	2.6604
coke (processed coal used in blast furnace)	20908	0.9714	29.50	0.93	2.8604	2.9446
crude oil	41816	1.4286	20.10	0.98	3.0202	2.1141
fuel oil	41816	1.4286	21.10	0.98	3.1705	2.2193
diesel	43070	1.4714	18.90	0.98	2.9251	1.9880
gasoline	42070	1.4714	19.50	0.98	3.0179	2.0510
diesel fuel	42652	1.4571	20.20	0.98	3.0959	2.1247
liquefied petroleum gas	50179	1.7143	17.20	0.98	3.1013	1.8091
petroleum	38931	1.3300	15.30	0.99	2.1622	1.6257

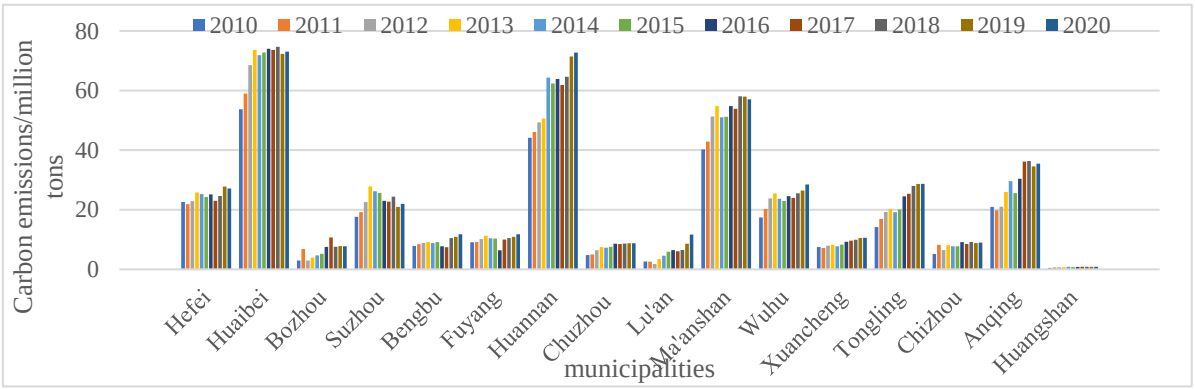


Figure 1. Carbon Emission Trends of 16 Prefectural-level Cities in Anhui Province

2.2. Method

Decoupling refers to the desynchronization of changes between economic growth and material consumption. Carbon decoupling refers to the reduction of carbon emissions while maintaining sustained economic growth. The Tapio decoupling analysis demonstrates the link between GDP,

consumption of energy substances and carbon dioxide emissions by taking into account a number of factors, i.e., the decoupling elasticity index:

$$\varepsilon = \frac{\Delta CO_2/CO_2}{\Delta E/E} \times \frac{\Delta E/E}{\Delta GDP/GDP} = \frac{\Delta CO_2/CO_2}{\Delta GDP/GOP} \quad (3)$$

In this equation ε represents the elasticity linkage coefficient between the carbon emissions of a region and the GDP of that place; $\triangle CO_2$ is the carbon variable of a region relative to the initial period of the calculation, and CO_2 is the amount of carbon emissions of a region which is in the initial period of the calculation; $\triangle$GDP is the variable of the Gross Domestic Product of a region relative to the initial period of the calculation, and the GDP is the specific value of the Gross Domestic Product of a region in the initial period of the calculation; $\triangle$E is the amount of the E is the change in end-use energy relative to the initial period of the calculation, and E is the amount of end-use energy consumed by a region relative to the initial period of the calculation. Tapio decoupling can be divided into eight different classes as given in Table 2.

Table 2. Eight different classifications of Tapio decoupling

decoupled state	degree of decoupling	Decoupling elasticity index	$\triangle CO_2$	$\triangle$GDP
decoupled	weakly decoupled	0≤ε<0.8	>0	>0
	strong decoupling	ε<0	<0	>0
	Recession decoupling	ε>1.2	<0	<0
negative decoupling	weak negative decoupling	0≤ε<0.8	<0	<0
	strong-negative decoupling	ε<0	>0	<0
	negative growth decoupling	ε>1.2	>0	>0
connect	Positively Connection	0.8<ε<1.2	>0	>0
	recession connection	0.8<ε<1.2	<0	<0

Table 3. The variables in Eq. (7)

considerations	Variable indicators	Description of variables
demographic	Carbon emissions C/million tons	Total carbon emissions from industrial production
	Population size P/million	Number of industrial employees at the end of the year
economics	Economic output Q/billion dollars	gross product of industry
	Economic level QP/(billion yuan-ten thousand people-1)	Industrial output per capita
technical level	Energy mix ES/%	Raw coal consumption/total energy consumption
	Energy intensity EE/(t standard coal-million yuan-1)	Total energy consumption/gross industrial output
	Carbon Emission Intensity TS/(million t-million yuan-1)	Total carbon emissions/gross industrial output

The prediction of carbon emissions is a key issue in determining the optimal carbon pathway. Ehrlich proposed the IPAT model in 1970, which reflects the combined effects of population, affluence, and technology and uses these parameters to predict a country's carbon emissions [14]. Its general form is shown as:

$$I = P \times A \times T \quad (4)$$

Here, I represents the annual carbon emissions of the region under study, P represents the population density of the region, A is the per capita affluence of the region, and T is the overall technology level of the region. However, the IPAT model has some defects, so York et al. improved the model with 2002 to 2003 and obtained the STIRPAT model [15, 16]. This model overcomes the shortcomings of the IPAT model where the independent variable affects the dependent variable to an equal degree, and also allows for the addition of other factors as required by the study to analyse the

impact on the accuracy of the results due to the fact that the original equation itself takes too few situations into account, and its general form is shown as:

$$I = eP^f A^g T^h x \tag{5}$$

Here, e is the constant term; f, g and h indicate the effect of each influence on the original equation, and x is used to balance the error caused by increasing the parameters of each influence. After replacing I with C, equation (5) is obtained by taking logarithms on both sides simultaneously:

$$\ln C = \ln e + f \ln P + g \ln A + h \ln T + x \tag{6}$$

Based on Zhang's study in 2022 [17], an extension and modification for Eq. (6) is made to obtain Eq. (7), which is modeled by the equation

$$\ln C = \ln a + e \ln P + f \ln Q + g \ln QP + h \ln ES + i \ln EE + j \ln TS + x \tag{7}$$

The variables in Eq. (7) are shown in Table 3. When using the STIRPAT model to study the changes in carbon emissions, there is a high degree of correlation between the data of each variable, such as the total industrial output value, total energy consumption and other data appearing many times in different independent variables, resulting in strong multicollinearity between the factor variables. In order to reduce the error in the model due to multicollinearity factors, ridge regression will be used to regress the carbon emission model. Compare the ridge regression coefficients from the regression of the model using ridge regression with the results obtained by Zhang in 2022 [17], and the errors were within manageable limits. After substituting each coefficient into Eq. (7) to obtain Eq. (8), the specific model is as follows:

$$\ln C = 6.071 + 0.147 \ln P + 0.135 \ln Q + 0.151 \ln QP + 0.153 \ln ES - 0.153 \ln EE - 0.154 \ln TS \tag{8}$$

Using the real industrial carbon emissions from 2005 to 2018 to compare with the predicted value of Eq. (8), the mean absolute value of the error is 0.086, which proves that the formula can be used, and the specific data are shown in Fig. 2.

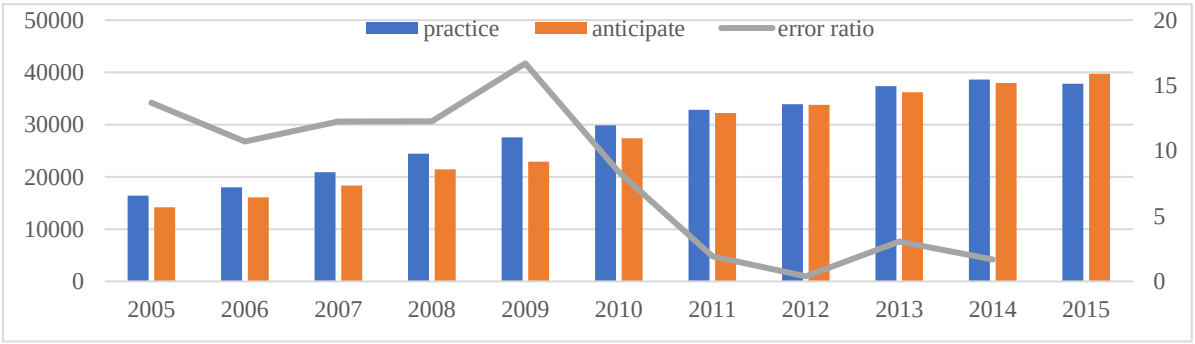


Figure 2. Comparison of projected and actual industrial carbon emissions in Anhui Province

3. Results and Discussion

3.1. Analyzing the Decoupled Relationship Using TAPIO Decoupling Analysis

The carbon emissions data of each region in Anhui Province between 2010 and 2020 have been obtained by calculation, and the decoupling elasticity index between carbon emissions and GDP of each prefecture-level city is calculated by using Eq. (3). To make the results easier to understand and analyse, the decoupling states are classified into the following forms, which are strong decoupling, weak decoupling, negative growth decoupling and growth connection. According to China's five-year planning policy, the time is set as two stages, 2011-2015 (Table 4) and 2016-2020 (Table 5).

Table 4. Decoupling status of cities from 2011 to 2015

area	Decoupling elasticity	△CO_2/CO_2	△GDP/GDP	decoupled state
Hefei	0.18	0.11	0.60	Weakly decoupled
Huaibei	0.70	0.23	0.33	Weakly decoupled
Bozhou	-0.46	-0.23	0.50	strong decoupling
Suzhou	0.64	0.34	0.53	Weakly decoupled
Bengbu	0.12	0.08	0.66	Weakly decoupled
Fuyang	0.22	0.12	0.54	Weakly decoupled
Huainan	2.91	0.35	0.12	Negative growth decoupling
Chuzhou	0.69	0.51	0.74	Weakly decoupled
Liu'an	3.25	1.27	0.39	Negative growth decoupling
Ma'anshan	0.86	0.19	0.22	Positively connected
Wuhu	0.29	0.13	0.45	Weakly decoupled
Xuancheng	0.37	0.16	0.43	Weakly decoupled
Tongling	0.86	0.19	0.22	Positively connected
Chizhou	-0.13	-0.06	0.48	Strong decoupling
Anqing	1.49	0.49	0.33	Negative growth decoupling
Huangshan	0.39	0.17	0.43	Weakly decoupled

Table 5. Decoupling status of cities from 2016 to 2020

area	Decoupling elasticity	△CO_2/CO_2	△GDP/GDP	decoupled state
Hefei	0.15	0.08	0.53	Weakly decoupled
Huaibei	-0.03	-0.01	0.35	Strong decoupling
Bozhou	0.04	0.02	0.50	Weakly decoupled
Suzhou	-0.1	-0.04	0.40	Strong decoupling
Bengbu	1.29	0.44	0.34	Negative growth decoupling
Fuyang	1.91	0.84	0.44	Negative growth decoupling
Huainan	0.42	0.14	0.33	Weakly decoupled
Chuzhou	0.04	0.02	0.45	Weakly decoupled
Liu'an	2.02	0.81	0.40	Positively connected
Ma'anshan	0.09	0.04	0.45	Weakly decoupled
Wuhu	0.38	0.16	0.42	Weakly decoupled
Xuancheng	0.3	0.15	0.45	Weakly decoupled
Tongling	0.94	0.17	0.18	Positively connected
Chizhou	-0.03	-0.01	0.38	Strong decoupling
Anqing	0.41	0.17	0.41	Weakly decoupled
Huangshan	0.05	0.02	0.43	Weakly decoupled

From 2011 to 2015, the 12th Five-Year Plan period, industrial carbon emissions and GDP in Anhui Province were weakly decoupled as a whole, with 9 out of 16 prefectural-level cities in a weakly decoupled state, 2 in a strongly decoupled state, 3 in a growth-negative decoupling, and 2 in a growth-connected state. The decoupling indices of Anqing, Lu'an, and Huainan are all greater than 1, indicating that the carbon emissions of industries above the scale have not been effectively controlled while the economy is growing. This may be directly or indirectly related to the fact that the GDP growth of Anqing and Lu'an is dependent on iron and steel smelting, and the economic growth of Huainan is dependent on the coal industry. The economic growth of these three cities is too dependent on carbon emissions and reasonable means and measures are needed to achieve climate change mitigation. From 2016 to 2020, the 13th Five-Year Plan period, Anhui Province's CO_2 emissions from industry and GDP as a whole continue to be weakly decoupled. Anqing has shifted from negative to weakly decoupled growth, and Huaibei and Suzhou have shifted from weak to strong decoupling, suggesting that optimising and adjusting the energy structure has begun to bear fruit. However, Bozhou changes from strong decoupling to weak decoupling, and Fuyang and Bengbu change from

weak decoupling to negative growth decoupling, indicating that the level of low-carbon economic development is not high, and the relationship between industrial carbon emissions and GDP fluctuates, which will bring more pressure to reduce emissions. Lu'an's decoupling elasticity index has been greater than 2, which may be related to its economy's long history of metallurgy, chemical and machinery manufacturing and its poor transition during the 13th Five-Year Plan. Lu'an also needs to continue to strengthen the share of the service sector in its economic development, while reducing its dependence on metallurgy and other industries, and appropriately adjusting its industry structure for balanced development.

The overall situation of the changes in the decoupling relationship between the "12th Five-Year Plan" and "13th Five-Year Plan" periods shows that most of the areas in Anhui Province are in a stable and weakly decoupled state, with less change in decoupling elasticity than that the "12th Five-Year Plan" period. The change is small, and the effect of emission reduction is not obvious enough. And in the weak decoupling and growth of negative decoupling of more cities, in order to reduce the pressure is still very big, should learn from the advanced experience of other provinces, and combined with the specific situation of different prefectural-level cities in the province, to make adjustments according to local conditions.

3.2. Analysis of Industrial Enterprises Above Scale Using the STIRPAT Model

Considering the many scenarios that will emerge in the future development of Anhui Province, from the dimensions of low-carbon economic development, energy use efficiency, low-carbon technological innovation, etc., and with reference to the "Outline of the Thirteenth Five-Year Plan for the National Economic and Social Development of Anhui Province" and the "Thirteenth Five-Year Plan for the Green Development of the Industry of Anhui Province", this paper estimates the trend of carbon emissions in Anhui Province from 2023 to 2040 with the aim of reducing the error of this model. According to the "Anhui Province Industrial Green Development Plan" and "Anhui Province Industrial Green Development "13th Five-Year Plan", to improve the accuracy of the prediction model. This paper will also refer to the change rule of indicators in previous years when setting up the scenarios, simulate the future changes of the six important reasons affecting carbon emissions, and construct different development scenarios on this basis to derive the change trend of carbon emissions in Anhui Province under different development situations. On this basis, different development scenarios are constructed to derive the trend of carbon emissions in Anhui Province under different development situations. Three development scenarios were set (seen from Table 6).

Table 6. Three situations

sight	P	Q	QP	ES	EE	TS
standard	2	2	2	2	2	2
extremist	3	3	3	3	3	3
energy conservation	1	1	1	1	1	1

Substituting the variables obtained through modeling combined with the three development scenarios into the improved model, i.e., Eq. (8), yields Fig. 3. In the standard model, CO_2 emissions from industrial activities in Anhui Province will grow at a moderate rate in the future when the number of industrial employees in the province shifts from a low rate of growth to a low rate of negative growth, the industrial output value and industrial output value per capita remain at an average level, and the energy intensity of the industry and the share of coal consumption in the energy structure decrease uniformly. The model predicts that carbon emissions from the industrial sector in Anhui Province will peak around 2035. The peak point is 493,256,700 tonnes, and after 2035 the annual carbon emissions from the industrial sector begin to gradually decrease downwards. In the radical model scenario, the number of people working in the industrial sector in Anhui Province in the future maintains low growth, influenced by factors such as the loss of young adults and the aging of society. At the same time, carbon emissions grow fastest when Anhui Province's industrial economic output and economic level exceeds the Chinese average and maintains high growth rates, when industrial energy intensity declines at a low rate, and when the proportion of raw coal consumed

in the energy mix remains high, and when carbon intensity declines at a low rate. This model predicts that the carbon emissions generated by the industrial sector in Anhui Province will keep the trend of increasing until 2040, and will reach the highest peak in 2040. The highest peak point is 562,487,300 tonnes, but after 2035, the total annual carbon emissions from industry begin to decelerate slowly.

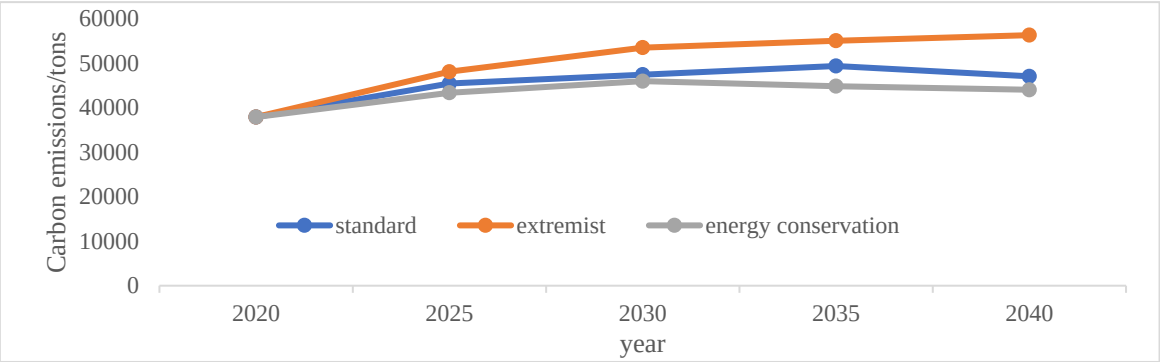


Figure 3. Annual carbon emission projections

In the scenario of energy conservation mode, the degree of mechanical automation in Anhui Province will rise in the future, the population trend will decline, which will affect the jobs provided by the industrial sector, and gradually reduce the number of people employed in the industrial sector will have a negative growth trend, at this time, the industrial economic output and the economic level of the industrial output to maintain a low rate of growth, industrial output value of the high rate of decline in energy consumption, coupled with new energy sources. At this time, the total volume and economic level of the industrial economy will maintain a low rate of growth, and the energy consumption of industrial output value will decline at a high rate, coupled with the vigorous development of new energy sources, the proportion of raw coal use in energy use will gradually decrease. According to the model prediction, carbon emissions from the industrial sector in Anhui Province will peak around 2030. By 2030, carbon emissions will rise from 378,717,900 tonnes to 459,270,000 tonnes. after 2030, the total annual carbon emissions from the industrial sector will begin to decline gradually, but the decline will be smaller than the growth.

4. Limitations and Prospects

There are some limitations to the conclusions drawn in this paper. When regressing the model using ridge regression and substituting the obtained ridge regression coefficients into the model, the absolute value of the error of the obtained results is high. It is possible to try to use other methods of quadratic operations on the coefficients to reduce the absolute value of the error in the results, so as to obtain a more realistic prediction result. At the same time, there is less planning for future development scenarios, and the simulation results are not comprehensive enough to cover the real carbon emissions in the coming decades. In the subsequent research, more methods will be used to reduce the error value of the model, trying to reduce the average value of the absolute error value to below 0.02. More development scenarios will also be added based on various situations in Anhui Province to ensure the comprehensiveness of the model as well as the credibility of the answers.

5. Conclusion

To sum up, the IPCC method is used to measure industrial CO_2 emissions and total carbon emissions in various regions of Anhui Province, to reveal regional differences in carbon emissions, and to analyse the decoupling relationship between GDP and carbon emissions in each region through the Tapio decoupling model. Meanwhile, based on the STIRPAT model, the parameters of industrial population size, total industrial economy, per capita industrial output value, energy structure, energy intensity and carbon emission intensity are set to construct a carbon emission prediction model for the industrial sector in Anhui Province, and three different scenarios of energy-saving, baseline and

aggressive are designed. In these three scenarios, the peak carbon emissions are 459.27 million tonnes, 493.25 million tonnes and 562.48 million tonnes, which will occur in 2030, 2035 and 2040 respectively. However, due to the limitation of data selection and incomplete modelling and scenario setting, the accuracy of the data is not perfect, but it is still in the usable range. The data can help local governments to better adjust their future policies according to the current and future status of their localities, and to achieve the purpose of mitigating climate change.

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