Analysis on the dynamic evolution of the equilibrium point of “carbon emission penetration” for energy-intensive industries in China: based on a factor-driven perspective

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Abstract
In order to achieve the carbon peaking and carbon neutrality goals, energy-intensive industries in China, as the main sectors of energy consumption and carbon emissions, had huge pressure to reduce emissions. In addition, the reduction of vegetation area led to a decline in carbon sink capacity, which further exacerbated the imbalance of mutual penetration between carbon source and carbon sink. Therefore, this article considered the role of carbon source and carbon sink and defined and calculated the “carbon emission penetration” (CEP) of the six energy-intensive industries from 2001 to 2020. The KAYA formula and the LMDI method were used to decompose the driving factors of CEP in the three aspects of scale, intensity, and structure. The combined model of STIRPAT and the environmental Kuznets curve (EKC) was used to simulate and analyze the equilibrium points of energy-intensive industries in China from the perspective of factor driving. The analysis results indicated that there were differences in the fluctuation trend of CEP in the six energy-intensive industries, which can be divided into three types: “two-stage growth,” “steady growth,” and “single peak.” Secondly, the driving factors from the three aspects of scale, intensity, and structure—emission intensity (CE), energy consumption intensity (EI), industrial structure (IS), economic scale (GP), and carbon sequestration scale (PCA)—had differences in industry and time dimensions. And the realization time of the CEP equilibrium points of six industries showed a three-level gradient feature significantly. This can provide some reference for the low-carbon transformation of six energy-intensive industries and optimization of China’s environmental management under the carbon peaking and carbon neutrality goals.

Keywords Energy-intensive industries · “Carbon emission penetration” · Equilibrium point · Dynamic evolution · Factor-driven

Highlights
• Define and calculate CEP of China’s six energy-intensive industries.
• The CEP trends of six industries: two-stage growth, steady growth, single peak.
• Analyze the difference of factors (CE, EI, IS, GP, PCA) on CEP of six industries.
• By simulating, the equilibrium time of CEP in six industries are gradient.

Introduction
Global warming is a common challenge facing all mankind in the new era. In recent years, with the rapid growth of the national economy, since China became a major carbon emitter in 2006, the carbon emissions have consistently ranked first in the world. In 2020, since the outbreak and rapid spread of COVID-19 around the world, the uncertainty of economic development has increased sharply (Wang et al. 2021), and it has also caused a certain impact on the environment. The growth rate of global emissions in 2020 slowed down, with carbon emissions reaching 32284.1 million tonnes (BP 2021). China’s carbon emissions in 2020 were 9899.3 million tons, accounting for 30.7% of the world’s emissions. At the same time, Wang and Su (2020) found that COVID-19 improved China’s carbon emission pressure in the short term. However, in the long run, when China fully lifts the blockade and resumes large-scale industrial
production, the greenhouse gas emissions may exceed pre-event levels. Therefore, under the background of economic development in the post-epidemic era, China’s emission reduction task is facing tremendous international pressure.

Under multiple pressures, as a major carbon emitter, China actively formulated corresponding low-carbon development goals and promoted the coordinated development of economic growth and environmental protection. The relevant goals and ambitions in recent years are shown in Table 1. Among them, in 2020, China announced at the General Debate of the Seventy-fifth United Nations General Assembly that it would reach peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (State Council of China 2020). And on October 26, 2021, the State Council issued the action plan for carbon peaking before 2030 (State Council of China 2021). After continuous efforts, China has achieved certain results in carbon emission reduction so far.

However, in the critical period of low-carbon development led by the carbon peaking and neutrality goals, China needs to accomplish carbon emission reduction tasks more efficiently. In order to effectively achieve the national emission reduction targets without sacrificing the development of the national economy, it is necessary to formulate corresponding policies based on the basic characteristics of China’s economic development and carbon emissions. Among the various industries in China, energy-intensive industries had huge carbon emissions and were the key targets of carbon emission reduction. According to the Statistical Communiqué of the People’s Republic of China on the 2010 National Economic and Social Development (National Bureau of Statistics 2011), the six energy-intensive industries are petroleum processing and coking, raw chemical materials and chemical products, nonmetal mineral products, smelting and pressing of ferrous metals, smelting and pressing of nonferrous metals, and production and supply of electric power, steam, and hot water. From the perspective of industrial emissions, energy-intensive industries in China had higher carbon emissions than other industries, and their carbon emissions accounted for more than 50% of the country’s carbon emissions, and they have maintained a growing trend (Fig. 1).

Excessive energy consumption and carbon emissions were important characteristics of energy-intensive industries. As a key participant in achieving the carbon peaking and carbon neutrality goals, can energy-intensive industries complete the emission reduction task, so as to contribute to the realization of the goals? This is worth researching. Lin and Tan (2017) analyzed the sustainable development potential of China’s energy-intensive industries from the

| Serial number | Target | Proposed time | Source |
|---------------|--------|---------------|--------|
| 1             | Peak carbon emissions by 2030 | December 12, 2015 | Paris Climate Conference |
| 2             | Peak carbon emissions by 2030 and carbon neutral by 2060 | September 22, 2020 | General debate of the seventy-fifth session of the United Nations General Assembly |
| 3             | China will formulate an implementation plan for striving to achieve peak carbon emissions by 2030 and carbon neutrality by 2060. | November 12, 2020 | Speech at the 3rd Paris Peace Forum |
| 4             | China will increase its nationally determined contribution, adopt stronger policies and measures, strive to achieve peak carbon emissions by 2030 and carbon neutrality by 2060 | November 17, 2020 | Speech at the 12th BRICS Summit |
| 5             | By 2030, China's carbon dioxide emissions per unit of GDP will drop by more than 65% compared with 2005, non-fossil energy will account for about 25% of primary energy consumption, and forest stock will increase by 6 billion cubic meters compared to 2005. | December 12, 2020 | Speech at Climate Ambition Summit |
| 6             | The “carbon peaking and carbon neutrality goals” goal is a major strategic decision made by the Party Central Committee after careful consideration. It is necessary to properly handle the relationship between development and emission reduction, overall and partial, short-term and medium-to-long-term | March 15, 2021 | The ninth meeting of the Central Financial and Economic Commission |
| 7             | By 2025, carbon emissions per unit of GDP will be 18% lower than in 2020. By 2030, carbon emissions per unit of GDP will be reduced by more than 65% compared with 2005, and the goal of peaking carbon emissions by 2030 will be achieved. | October 26, 2021 | Carbon Peak Action Plan by 2030 |
perspective of carbon emission factors. Chen and Wu (2022) dynamically analyzed the change in growth rate of carbon emission efficiency of energy-intensive industries. Liu et al. (2019) studied regional differences in the impact of energy-intensive industries on China’s carbon emissions. Previous studies have indeed done a lot of work on carbon emissions of energy-intensive industries, but there were still research gaps in that they hardly considered carbon sinks. However, in order to achieve carbon peaking and carbon neutrality goals, it is necessary to increase carbon sinks while reducing emissions. At present, with the acceleration of industrialization and urbanization, the stability of the ecosystem was gradually being destroyed. Deforestation, grassland degradation, land desertification, and soil erosion have occurred more and more frequently, and the threat to the ecosystem has become more and more serious. Green vegetation had good carbon sequestration ability and can help to reduce the greenhouse effect (Wu et al. 2020b). However, the reduction of vegetation area led to the decline in China’s green carbon sequestration capacity, which further exacerbated the imbalance of mutual penetration between carbon sources and carbon sinks. In the short term, environmental problems caused by rising carbon emissions will continue to restrict economic development and will not be conducive to achieving the carbon peaking and carbon neutrality goals. Considering that there were few studies on carbon emissions of energy-intensive industries from the two perspective of carbon emissions and carbon sinks, this paper considered adding carbon sink capacity on the basis of studying carbon emissions in energy-intensive industries.

Therefore, the motivation and contribution of our study were outlined as follows: First, the study defined and calculated the “carbon emission penetration” (CEP) of the six energy-intensive industries from 2001 to 2020. By calculating the CEP of the six energy-intensive industries, the characteristics of the fluctuation and evolution of the CEP between different industries from 2001 to 2020 could be described. Second, based on the KAYA formula and the LMDI method, this paper decomposed and analyzed the driving effects of five factors for CEP of the six energy-intensive industries in three categories: scale, intensity, and structure. Third, this paper combined the STIRPAT and EKC, based the impact of driving factors on the CEP of the six energy-intensive industries and the future development of each factor, and set up a low-carbon scenario to simulate and analyze the equilibrium points of the CEP of the six energy-intensive industries. Fourth, based on the gradient characteristics of the time when the CEP equilibrium point of the six energy-intensive industries was reached, this paper provided policy suggestions for formulating differentiated industry low-carbon development strategy and improving the industry’s emission reduction efficiency to realize the carbon peaking and carbon neutrality goals.
The remaining parts of the paper were arranged as follows: the “Literature review” section included the literature review. Methods and data sources were presented in the “Data and methodology” section. The “Results and discussion” section conducted results analysis and discussion from various perspectives. Conclusions were presented in the “Conclusions and policy implications” section, and based on these conclusions, this study proposed some policy implications.

Literature review

The proposal of the carbon peaking and carbon neutrality goals had a profound impact on the development of China and the world. However, at present, carbon emission pressure of China is huge, especially under the carbon peaking and carbon neutrality goals, and more contributions need to be made to achieve the goals. The literature review of this paper was carried out from three aspects: first, summarized the related researches on carbon pressure and drew on the idea of carbon pressure research to put forward the concept of CEP of energy-intensive industries in this paper; second, summarized the relevant research on the decomposition of carbon emission factors and, on this basis, determined the decomposition methods and factors for the CEP of energy-intensive industries in this paper; and third, summarized the relevant research on carbon emission peak analysis and clarified the analysis method of the CEP equilibrium point of energy-intensive industries in this paper. The details were as follows.

Regarding the research on carbon pressure, domestic and foreign researchers discussed the regional carbon pressure. Liang and Xu (2017) comprehensively evaluated the balance relationship between carbon activities and the ecological environment under different regional scenarios and comprehensively judged the temporal and spatial distribution characteristics of carbon pressure at the provincial level and its center of gravity change trend. Chen et al. (2020a) introduced net primary productivity to establish a carbon footprint pressure index to analyze carbon pressure. Cheng et al. (2020) optimized carbon emission reduction index (CERI) model, which assessed the pressure at the national, provincial, and municipal levels. Chen et al. (2021) decomposed and studied the carbon balance pressure index based on plant carbon sequestration in 77 countries around the world. To sum up, previous studies have indeed done a lot of work on regional carbon pressure, but there was still the research gap which there was very little research on industry carbon pressure research. Therefore, the situation of industry carbon pressure of China needed to be explored urgently. Energy-intensive industries required more attention, as the key link in the industrial chain and the main source of China’s CO₂ emissions. However, the current multiscale analysis of carbon pressure under the resource and environmental constraints of the six energy-intensive industries was insufficient. Therefore, this article took China’s six energy-intensive industries as the research objects, and drew on the ideas of regional carbon pressure calculation and analysis, innovatively introduced the concept of “carbon emission penetration” (CEP) in energy-intensive industries, and analyzed their level and fluctuation evolution characteristics.

Regarding the literatures on the decomposition of carbon emission factors, there were currently many domestic and foreign researches on the analysis of carbon emission driving factors. The common factor decomposition models included the structural decomposition method (SDA) (Wang et al. 2017; Hastuti et al. 2021), index decomposition method (especially LMDI) (Liu et al. 2007), and Kaya formula (Kaya 1990). These models have been widely used in carbon emissions research due to their respective advantages and scope of application. Hasan and Chongbo (2020) estimated energy-related carbon dioxide emissions growth in Bangladesh using the LMDI method. In recent years, researchers conducted more in-depth discussions on the driving factors of industrial carbon emissions. Among them, energy consumption intensity was the main indicator for reducing carbon emissions (Jin and Han 2021), and the expansion of industrial scale was the leading force driving the increase in carbon emissions (Du et al. 2018), and it was most significant in the power industry. Udemb et al. (2020) found positive correlations between carbon emissions and energy consumption, foreign direct investment, and population in addition to economic growth. In addition, various factors such as technological innovation (Dong et al. 2022), economic development (Lai et al. 2019; Sun et al. 2021), policies and regulations (Jiang et al. 2019; Song and Zhou 2021), foreign trade (Boamah et al. 2017; Wang and Zhang 2021), and urbanization (Wang and Su 2019) also had a significant impact on industrial carbon emissions. For example, Hasan and Raza (2022) studied the relationship between natural gas consumption and economic growth with carbon emissions. Wang et al. (2022b) explored the impact of urbanization and found that urbanization strengthened the positive relationship between the economy and carbon emissions and ecological footprint. To sum up, the previous studies on the decomposition and analysis of carbon emission factors provided the reference for the study of the factors in this paper. In order to explore the influence of different factors on the CEP of energy-intensive industries innovatively proposed in this paper, this paper drew on the method of decomposition of carbon emission factors and selected the KAYA formula and LMDI method to decomposition and analyze the CEP of energy-intensive industries. At the same time, the factors were decomposed from the three aspects of scale, intensity, and structure and combined with the concept of CEP, the factor named “carbon sequestration scale” was innovatively proposed.
The literature studies on carbon emission peak analysis were as follows. Most of the previous literatures on carbon emission peaks were based on factor analysis to make predictions, usually through the STIRPAT model or the environmental Kuznets curve (EKC) model. In terms of STIRPAT model application, Zhang et al. (2020) analyzed the peak carbon dioxide in China’s Yunnan Province through the regression analysis of population, wealth, and technology (STIRPAT) and the long-term energy replacement planning system (LEAP) model. Wen et al. (2022) analyzed China’s carbon neutrality scenarios based on STIRPAT and system dynamics models and found 8 pathways that were in line with China’s current goal of achieving carbon neutrality. Chen et al. (2022) simulated and predicted carbon emissions in major regions of China based on the STIRPAT and ARIMA models. Ziyuan et al. (2022) predicted the peak carbon emission in Xinjiang based on the combination of STIRPAT model and neural network. In terms of EKC model application, Chen et al. (2020b) predicted the peaks of the four carbon pillar sectors (i.e., industry, construction, transportation, and agriculture), using carbon Kuznets curve (CKC) model based on the EKC hypothetical. Fang et al. (2022a) used regression analysis and Monte Carlo simulation to study the EKC hypothesis of eight sectors in the past 23 years and found that the emissions from agriculture, construction, manufacturing, and transportation are likely to reach peaks before 2030, while the power and mining industries may reach after 2030. Through comparison, Lin and Jiang (2009) found that the traditional EKC model predicted peak carbon emissions only considering the impact of per capita income, while energy intensity, industrial structure, and energy consumption structure all had the significant impact on carbon dioxide emissions; this led to inconsistencies between the empirical prediction and the theoretical inflection point of the CKC model. In addition, other methods were also applied to the prediction of carbon emission peaks. For example, Fang et al. (2022b) combined gray prediction and NAR neural network to study the carbon emission peak in China. To sum up, previous studies did a lot of work in the analysis of carbon emission peaks, which provided a reference for the analysis of the CEP equilibrium point of energy-intensive industries in this paper. Therefore, by referring to the definition of “carbon pressure” in various literatures, this article defined and calculated the CEP of the six energy-intensive industries, and on this basis, characterized the evolution feature of the CEP fluctuations between different industries. The KAYA and LMDI methods were further used to analyze the driving factors of the CEP of the six energy-intensive industries. Based on the historical trends and driving factors of CEP, a low-carbon simulation scenario was set up to analyze the equilibrium points of the CEP of the six energy-intensive industries in China. So as to put forward some reasonable references for the early realization of the national total carbon emissions carbon peaking and carbon neutrality goals. The research process and of the research in this paper is shown as follows Fig. 2.

**Data and methodology**

Based on the study of the definition of carbon pressure, this article drew on the research ideas, defined and calculated the CEP of the six energy-intensive industries, and on this basis, characterized the evolution feature of the CEP fluctuations between different industries. The KAYA and LMDI methods were further used to analyze the driving factors of the CEP of the six energy-intensive industries. Based on the historical trends and driving factors of CEP, a low-carbon simulation scenario was set up to analyze the equilibrium points of the CEP of the six energy-intensive industries in China. So as to put forward some reasonable references for the early realization of the national total carbon emissions carbon peaking and carbon neutrality goals. The research process and of the research in this paper is shown as follows Fig. 2.

**Data source**

This study took 2001–2020 as the observation period. The data required for analysis of the six energy-intensive industries (Table 3) mainly fall into four categories:

1. **The carbon emission data C_i** of each industry. The data came from the data published in the China Carbon Accounting Database (CEADs) (Shan et al. 2018). The industry carbon emission C_i in the database is based on the carbon emission calculation formula published by the IPCC, which included the emission of 17 kinds of fossil fuels burned in 47 socio-economic sectors and the emission of cement production.
2. **Energy consumption data E_i (standard quantity)** of each industry. The initial data came from the “energy consumption by industry” in the China Statistical Yearbook.
| Dimension                        | Object                                                                 | Methodology                                                                 | Author                      |
|---------------------------------|------------------------------------------------------------------------|-----------------------------------------------------------------------------|-----------------------------|
| Carbon pressure                 | Carbon pressure at the provincial in China                            | Carbon pressure center of gravity calculation model                         | Liang and Xu (2017)         |
|                                 | Carbon pressure in 60 countries globally                              | Carbon footprint pressure index model                                        | Chen et al. (2020a)         |
|                                 | Carbon pressure at the national, provincial, and municipal levels in China | Carbon emission reduction index (CERI) model                                 | Cheng et al. (2020)         |
|                                 | Carbon pressure in 77 countries globally                              | Carbon balance pressure index model                                         | Chen et al. (2021)          |
|                                 | CO₂ emissions in Guangdong, economic and population growth, emission intensity, international trades | SDA                                                                         | Wang et al. (2017)          |
| Decompose carbon emission factors | CO₂ emission changes in Indonesia, energy intensity, carbonization factor, technology, structural demand, consumption effect, scale effect | SDA                                                                         | Hastuti et al. (2021)       |
|                                 | China’s industrial CO₂ emissions, energy intensity, industrial structural, industrial activity, final fuel shift | LMDI                                                                        | Liu et al. (2007)           |
|                                 | CO₂ emission, GNP growth                                              | Kaya formula                                                                | KAYA (1990)                 |
|                                 | CO₂ emissions in Bangladesh, economic growth, unemployment, services, urban population | LMDI                                                                        | Hasan and Chongbo (2020)    |
|                                 | CO₂ emissions in China’s manufacturing industry, investment carbon intensity, energy consumption intensity | Generalized Divisia Index Model (GDIM)                                      | Jin and Han (2021)          |
|                                 | CO₂ emissions in six energy-intensive industries, industrial scale, energy consumption intensity | LMDI                                                                        | Du et al. (2018)            |
|                                 | CO₂ emissions, population, economic, foreign direct investment, energy consumption | Pesaran’s autoregressive distributed lag–bound test, Granger causality analysis | Udemb et al. (2020)         |
|                                 | CO₂ emissions, technological innovation                                | spatial mediation model, spatial moderation model                            | Dong et al. (2022)          |
|                                 | CO₂ emission of construction industry in China, energy consumption, economy growth | improved Kaya model                                                          | Lai et al. (2019)           |
|                                 | China’s CO₂ emissions, economic growth, green energy technology       | EKC                                                                         | Sun et al. (2021)           |
|                                 | CO₂ emission from US sector, economic policy                          | standard linear Granger causality test, nonlinearity BDS tests              | Jiang et al. (2019)         |
|                                 | Chinese manufacturing CO₂ emission, industrial policy                 | regression analysis model                                                   | Song and Zhou (2021)        |
|                                 | China’s CO₂ emission, urbanization, industrialization                 | Tapio model, Johansen cointegration theory, Granger causality test           | Wang and Su (2019)          |
|                                 | CO₂ emissions of 134 countries, urbanization                          | EKC theory, threshold regression model                                       | Wang et al. (2022b)         |
|                                 | CO₂ emissions in Bangladesh, natural gas consumption, economic growth | Autoregressive distributed lag (ARDL), Vector Error Correction Model (VECM) | Hasan and Raza (2022)       |
| Peak carbon emission            | Peak carbon emissions in China’s Yunnan Province                       | STIRPAT, LEAP                                                              | Zhang et al. (2020)         |
|                                 | China’s carbon neutrality scenarios                                   | STIRPAT, system dynamics                                                   | Wen et al. (2022)           |
|                                 | Peak carbon emissions in major regions of China                       | STIRPAT, ARIMA model                                                       | Chen et al. (2022)          |
|                                 | Peak carbon emissions in Xinjiang                                     | STIRPAT, neural network                                                    | Ziyuan et al. (2022)        |
|                                 | Peaks carbon emission of four sectors in China                        | Carbon Kuznets curve (CKC) model                                            | Chen et al. (2020b)         |
|                                 | Peaks carbon emission of eight sectors in China                       | EKC, regression analysis, Monte Carlo simulation                           | Fang et al. (2022a)         |
|                                 | Peak carbon emissions in China                                        | EKC                                                                         | Lin and Jiang (2009)        |
|                                 | Peak carbon emissions in China                                        | Gray prediction, NAR neural network                                         | Fang et al. (2022b)         |
(3) GDP and each industrial added value of energy-intensive industries (GDPi). The data came from the China Statistical Yearbook and the Statistical Yearbook of China’s industry. Since the National Bureau of Statistics no longer released industrial value-added data for industrial sub-sectors after 2007, the industrial value-added of energy-intensive industries from 2008 to 2020 was calculated from the official annual growth rate of industrial value-added, which was from the Statistical Communique of the People’s Republic of China on the National Economic and Social Development.

(4) Population (P), forest area ($A_{1i}$), and grassland area ($A_{2j}$). The data mainly came from the China Statistical Yearbook and the website of the National Bureau of Statistics.

Definition and calculation of CEP in energy-intensive industries of China

The concept of stress in the field of economics originated from the economists Mark Ealing and Liu Ying of the Bank of Canada. They first proposed the concept of “financial stress” when studying the risks of the North American financial market. They constructed a financial stress index to measure the systemic risk of the financial market (Apostolakis and Papadopoulos 2014). Since then, the academic community put forward the concepts of fiscal pressure, arable land pressure, water resource pressure, ecological pressure, etc., and conducted related research. Carbon pressure was proposed on the basis of ecological pressure research. Most research generally defined the meaning and boundary of carbon pressure on the basis of calculating carbon emissions and carbon carrying capacity. They defined carbon pressure mainly to refer to the ratio of regional energy consumption carbon emissions to regional carbon sink capacity, which directly reflected the degree of carbon emission pressure faced by the regional ecological environment.

The “carbon emission penetration” (CEP) of energy-intensive industries proposed in this study was a concept derived from the idea of carbon pressure, which referred to the negative impact of industry input and output changes caused by the industry itself or policy regulation on the...
carbon balance of China’s entire ecosystem. We thought the CEP of energy-intensive industries was the product of mutual action including the external influence of macroeconomic policies, the impact of the industry’s own input and output, and the fragile structure of the ecosystem. Taking into account the current situation of China’s carbon emission reduction and the complexity of macro-control, it was necessary to construct an industrial CEP index to measure the carbon pressure of energy-intensive industries. Through horizontal and vertical comparisons of the industry’s CEP, it can measure the impact of energy-intensive industries’ carbon emissions on the environment, and provide relevant references for effectively responding to climate change and achieving the carbon peaking and carbon neutrality goals.

This study drew on the concept of carbon pressure and defined the CEP indicator to measure the intrusive impact of large amounts of carbon emissions from energy-intensive industries on the balance of China’s atmospheric environment. Compared with the absolute indicator of carbon emissions, CEP took into account the relative factor of the environment’s ability to absorb carbon and can more comprehensively assess the balance between human “carbon activities” and the natural environment. The “carbon absorption capacity” referred to the carbon sequestration capacity of terrestrial ecosystems, mainly from the deposition of fossil fuels and the photosynthesis of plants in forests, grasslands, gardens, and cultivated land. As the carbon fixed by arable land and gardens would be converted and harvested, it decomposed in a short time. While forests and grasses were the main carbon sinks, accounting for 93% of the total carbon sinks storage. Therefore, most studies only considered the area of forest and grassland when calculating carbon absorption capacity. Fu et al. (2020) took the ecologically fragile area of Yunnan as an example, established the carbon footprint and vegetation carbon carrying capacity model, selected forests, grasslands, and crops to calculate carbon carrying capacity, and evaluated the level of carbon security. The specific calculation formula and related carbon absorption coefficient mainly used the results of the study by Xie et al. (2008).

### Table 3 China’s energy-intensive industries and their industry serial number

| Industry serial number | Industry name                                   |
|------------------------|------------------------------------------------|
| Industry1              | Petroleum Processing and Coking                 |
| Industry2              | Raw Chemical Materials and Chemical Products    |
| Industry3              | Nonmetal Mineral Products                       |
| Industry4              | Smelting and Pressing of Ferrous Metals         |
| Industry5              | Smelting and Pressing of Nonferrous Metals      |
| Industry6              | Production and Supply of Electric Power, Steam, and Hot Water |

In the formula, \( CA \) is the maximum mass capacity of \( \text{CO}_2 \) that forests and grasslands in China’s statistical area can bear in a certain period of time; \( A_1 \) and \( A_2 \) represent the area of forest and grassland, respectively. The carbon absorption capacity coefficients \( S_1 \) and \( S_2 \) of forest and grassland were 3.809592 t/hm\(^2\) and 0.949483 t/hm\(^2\), respectively.

Based on the calculation of carbon emissions and carbon absorption capacity (Chen et al. 2021), according to the definition of CEP in this study, the calculation model of CEP can be set as:

\[
C_{EP} = \frac{C}{CA} \quad \text{(2)}
\]

If \( C_{EP} > 1 \), it indicated that the carbon emission was “overloaded” relative to the carbon absorption capacity of the ecosystem, the CEP was too large, and the carbon cycle system was facing ecological deficit pressure; if \( C_{EP} < 1 \), it indicated that the carbon emissions were within the carrying range of the ecosystem, the CEP was small, and the carbon cycle system still had an ecological surplus; if \( C_{EP} = 1 \), carbon emissions and ecological carbon sequestration capacity were relatively equal, and the CEP was acceptable, which was at the critical point of “carbon overload.”

### The factor decomposition model of CEP in energy-intensive industries of China based on the KAYA and LMDI

A large number of decomposition methods were widely used to study the driving force of carbon emission changes during a period of time. Although there were quite a few decomposition methods, Ang et al. (2003) believed that the LMDI method was the best method because it had unparalleled advantages in theoretical basis, ease of use, and result interpretation. And many researchers practiced LMDI techniques to analyze \( \text{CO}_2 \) emissions (Hasan and Chongbo 2020) and energy use (Hasan and Liu 2022) in various regions and countries. Therefore, this article would use the LMDI to decompose the factors of the CEP in six energy-intensive industries based on the KAYA formula and study the factors of the CEP internal laws and characteristics. According to the KAYA formula (Kaya 1990), the carbon emissions of each industry can be decomposed as follows:

\[
C_{EP} = \frac{C_{i}}{CA} = \frac{C_{i}}{E_{i}} \times \frac{E_{i}}{GDP_{i}} \times \frac{GDP_{i}}{P} \times \frac{P}{CA} \quad \text{(3)}
\]

In the formula, \( C_{i} \) was the carbon emissions produced by the \( i \)-th industry, \( 10^4 \) tons; \( E_{i} \) represented the total amount of standard coal equivalent to the energy consumption of the
\[ CEP = CE \times EI \times IS \times GP \times PCA \]  

\( (4) \)  

According to the LMDI additive decomposition method of Ang et al. (2003), the base period and calculation period were represented by \( B \) and \( T \) respectively, and Formula (4) was decomposed to obtain:

\[ \Delta CEP = CEP^T - CEP^B = \Delta CEP_{CE} + \Delta CEP_{EI} + \Delta CEP_{IS} + \Delta CEP_{GP} + \Delta CEP_{PCA} \]  

\( (5) \)

Among them, the emission intensity effect:

\[ \Delta CEP_{CE} = \frac{CEP^T - CEP^B}{\ln CEP^T - \ln CEP^B} \times \ln \frac{CE^T}{CE^B} \]  

\( (6) \)

Energy consumption intensity effect:

\[ \Delta CEP_{EI} = \frac{CEP^T - CEP^B}{\ln CEP^T - \ln CEP^B} \times \ln \frac{EI^T}{EI^B} \]  

\( (7) \)

Industrial structure effect:

\[ \Delta CEP_{IS} = \frac{CEP^T - CEP^B}{\ln CEP^T - \ln CEP^B} \times \ln \frac{IS^T}{IS^B} \]  

\( (8) \)

Economic scale effect:

\[ \Delta CEP_{GP} = \frac{CEP^T - CEP^B}{\ln CEP^T - \ln CEP^B} \times \ln \frac{GP^T}{GP^B} \]  

\( (9) \)

Scale effect of carbon sequestration:

\[ \Delta CEP_{PCA} = \frac{CEP^T - CEP^B}{\ln CEP^T - \ln CEP^B} \times \ln \frac{PCA^T}{PCA^B} \]  

\( (10) \)

By combining the KAYA formula and the LMDI method, the total changes in six industrial CEP can be decomposed into five factors: emission intensity (CE), energy consumption intensity (EI), industrial structure (IS), economic scale (GP), and carbon sequestration scale (PCA) (Table 4). On the basis of general research on the driving factors of carbon emissions, we fully considered the impact of carbon emission and carbon sequestration capacity and innovatively introduced the scale effect of carbon sink. From the two aspects of carbon emission and carbon sink, which can achieve the detailed description to the internal factors of the CEP of each energy-intensive industry.

In order to express the contribution of each factor to the CEP from the base period to the T period, the contribution rate (CR) was proposed as follows:

\[ CR = \frac{\Delta CEP_{CE} + \Delta CEP_{EI} + \Delta CEP_{IS} + \Delta CEP_{GP} + \Delta CEP_{PCA}}{\Delta CEP} \]  

\( (11) \)

The equilibrium point analysis model of the CEP in energy-intensive industries of China based on the STIRPAT and EKC

The STIRPAT model is generally expressed as \( I = a P^b A^{C T} d_e \), the random special form proposed by York, Dietz, Rosa, and others based on the I-PAT model (Su and Lee 2020). Among them, I, P, A, T represent environmental impact, demographic factors, wealth factors, and technical factors, respectively; \( a \) is the model
coefficient; \( b, c, \) and \( d \) are respectively population and wealth and the coefficient of technical factors; and \( e \) is the random error term (Zhang et al. 2020). Since the STIRPAT model is a non-linear multivariate equation, in order to facilitate the calculation, take the logarithm of both sides of the equation at the same time to transform it into a linear model, that is \( \ln I = \ln a + b \ln P + c \ln A + d \ln T + \ln e \). It can be seen that the STIRPAT model considers the impact of changes in population, wealth, and technological factors on the environment and eliminates the impact of the problem of changes in the same proportion. Therefore, this model is suitable for the measurement analysis of the equilibrium point of the CEP in China’s energy-intensive industries.

EKC is a classic model for studying the relationship between environmental quality and income. EKC reveals that the environmental quality begins to degrade with the increase of income, and the income level rises to a certain extent and then improves with the increase of income, that is, the relationship between environmental quality and income is an inverted U shape (Haseeb et al. 2018; Jiang et al. 2021). The general format of its model assumptions is as follows:

\[
\ln I = \alpha + \beta_1 \ln Y + \beta_2 (\ln Y)^2 + \varepsilon
\]  

(12)

Among them, \( \alpha \) represents a constant variable, \( E \) represents environmental quality, \( Y \) represents GDP per capita, and \( \varepsilon \) is a standard error term. \( \beta_1 \) and \( \beta_2 \) represent estimation coefficients.

In order to find out the equilibrium point of the CEP of China’s six energy-intensive industries, this paper combined the characteristics of the inverted U shape of the EKC model, adopted the EKC model to the income factor of the STIRPAT model, and established the analysis and measurement model for the CEP equilibrium of the six energy-intensive industries in China. The model was as follows:

\[
\ln CEP = \alpha + \beta_1 \ln CE + \beta_2 \ln EL + \beta_3 \ln IS + \beta_4 \ln GP + \beta_5 (\ln GP)^2 + \beta_6 \ln PCA + \varepsilon
\]  

(13)

Furthermore, we analyzed the equilibrium points of CEP of the six energy-intensive industries through scenario simulation. When \( \ln CEP \) was taken as the zero point, CEP was 1, and the CEP reached equilibrium. Scenario simulation was based on the analysis of history and current situation to simulate the future economic and social development (Wang et al. 2022a), and realized the simulation of the future by substituting expected parameters into the model.

### Results and discussion

#### The fluctuation and evolution characteristics of the CEP in energy-intensive industries of China

This study took 2001–2020 as the research period and obtained the annual data series of the CEP in China’s energy-intensive industries through Formulas (1)–(2). Based on this result, we analyzed the fluctuation evolution characteristics of the CEP of China’s energy-intensive industries (Fig. 3).

It can be seen from Fig. 3 that the overall CEP of the six energy-intensive industries showed a trend of first rising sharply and then fluctuating. The overall CEP of energy-intensive industries increased from 2001 to 2013 as a whole. During this period, since 2002, the CEP growth rate of China’s energy-intensive industries had increased significantly and showed the upward trend year by year, with the average growth rate of 7.99%. And this was the highest growth rate in 2003 compared with 2002, reaching 17.69%, into the high-speed growth stage, mainly because China’s large-scale infrastructure construction and urbanization in the past 10 years promoted the increase of China’s carbon emissions. This is mutually confirmed with the research of Yuan and Zhao (2016). Large-scale infrastructure construction activities consume a large amount of energy-intensive materials and electricity, and the construction industry led to large-scale indirect emissions from the six energy-intensive industries. By 2013, the CEP had reached 146.79% of 2001, reaching a staged peak. However, during this period, 2008 was special. Affected by the global financial crisis, China’s economic downturn drove the reduction of carbon emissions in the industries of the national economy, and a short-term decline in the CEP. And then due to the government’s economic stimulus plan to economic growth, carbon emissions in various industries rebounded again (Wang et al. 2021). After 2013, the total CEP of China’s energy-intensive industries basically remained at about 7.5, entering the stage of stable development. The main reason was that during this period, China achieved some positive results in promoting the development of enterprises with the concepts of “circular economy” and “green growth” and other environmentally friendly policies. This is mutually confirmed with the research of Wu et al. (2020a).

In terms of different industries, there were some differences in the changing trends of the CEP of China’s six energy-intensive industries from 2001 to 2020, which can be divided into three types: “two-stage growth,” “steady growth,” and “single peak.” In the research time interval, without considering the impact of the 2008 financial crisis, the “two-stage growth” industries reflected significant segmented feature. After reaching a phased peak and trough during the 12th Five-Year Plan period, it continued to grow again at a higher rate. The industry 4 and the industry 6 were representatives of this type. For the “steady growth” industry, after reaching a peak for a period of time, the CEP of the industry fluctuated around an average level and gradually stabilized. The industry 1 and industry 5 showed significant “steady growth” characteristics. The “single peak” industries’ CEP...
reached a peak during the research period, and then gradually declined. The industry 2 and the industry 3 showed significant “single peak” characteristics. This is corroborated with the research of Chen and Wu (2022), which found that after 2015, the emissions of Raw Chemical Materials and Chemical Products (industry 2 in the paper) tended to be stable and showed a slight downward trend.

**The effect of the driving factors of the CEP in China's energy-intensive industries**

Based on the results of the CEP in China’s energy-intensive industries from 2001 to 2020, this section used Formulas (3)–(11) to calculate the contribution of five driving factors (CE, EI, IS, GP, PCA) to the changes in CEP of six industries (Fig. 4). It was found that the five driving factors had different directions and degrees of effect, and there were differences in different periods and between different industries.

Generally speaking, from the perspective of the direction of each driving factor, economic scale (GP) factors mainly played a positive driving effect, and carbon intensity (CE), energy consumption intensity (EI), and carbon sequestration scale (PCA) mainly played a negative driving role. While the driving directions of the industrial structure (IS) for different industries were quite different, it needed to be analyzed for specific industries. From the perspective of the size of the driving factors, the contribution of CE, EI, IS, and GP were relatively large, while the contribution of PCA was relatively small.

Specifically, in terms of the scale factors GP and PCA, compared with other factors, the GP had the most prominent impact on the six energy-intensive industries, and the changes in the CEP of each industry were basically positively driven, indicating that the rapid economic growth was the main driving force. This is consistent with the study of Fei et al. (2011), which found that economic development was positively related to carbon emissions. However, there was no significant difference in the degree of the GP affecting the six industries. In comparison, the driving effect of the PCA from 2001 to 2020 was relatively weak, with the contribution rate of basically less than 10%. This was mainly because the overall natural carbon sink in China has remained stable in the past 20 years, with a slight increase year by year, and the forest and grassland carbon sinks selected in this paper were huge but grew slowly, mainly from historical stocks (Wen at al. 2022). Regarding the PCA, the reciprocal was taken in the article. When the value was

Fig. 3 Annual data series of the CEP in energy-intensive industries from 2001 to 2020

- Total Consumption
- Production and Supply of Electric Power, Steam and Hot Water
- Smelting and Pressing of Nonferrous Metals
- Smelting and Pressing of Ferrous Metals
- Nonmetal Mineral Products
- Raw Chemical Materials and Chemical Products
- Petroleum Processing and Coking
positive, it indicated that the change promoted the weakening of the industries’ CEP. The driving effect of the PCA on the CEP of the energy-intensive industries had a little difference.

In terms of the intensity factors EI and CE, the EI showed the negative driving effect on changes in industrial CEP after 2005. It showed that the EI was the main factor that promoted the reduction of the CEP of the industries, which is consistent with the findings of Du et al. (2018), especially for the production and supply of electric power, steam and hot water (industries 6) and the petroleum processing and coking (industries 1), the contribution of EI was very high. The driving effect of CE on the CEP of the six energy-intensive industries was significantly dissimilated into three categories. Taking 2005 as the dividing line, the first category of industries was significantly negatively driven by CE after 2005, such as industry 1, 2, and 6. The second category of industries received significant positive driving effects from CE after 2005, such as industry 3 and industry 4. There was another type of industry that received the significant positive driving effect of CE before 2010, and the significant negative driving effect of CE after 2010, such as industry 5. The main reason was because that the implementation of China’s policy to adjust the energy consumption structure promoted cleaner energy consumption structure, leading to some certain degree of intensity effect.

In terms of the structure factor IS, the driving directions of various industries of the industrial structure (IS) were inconsistent, and different stages showed inconsistent effects. This corroborated with the research of Jin and Han (2021). When the value was positive, it indicated that changes in the industrial structure are not conducive to the reduction of the industries’ CEP. The driving effect of the IS on the CEP of the six energy-intensive industries was significantly dissimilated into two categories. Industries 1 and 6 were mainly driven by their positive driving effects before 2005, and by their negative driving effects after 2005. Industries 2, 3, 4, and 5 were mainly affected by their negative driving effects before 2005, and were mainly affected by their positive driving effects after 2005. This was closely related to the national industrial structure adjustment policy. After 2005, the proportion of the output value of industry 1 and 6 in the total output value showed the significant downward trend. For example, the proportion of the output value of the industry 6 dropped from 7.92% in 2005 to 4.87% in 2019, and the proportion of the output value of the industry 1 fell from 2.75% in 2005 to 1.62% in 2019, while the proportion of the output value of the other four energy-intensive industries showed the fluctuating upward trend.

Analysis of the equilibrium point of the CEP in China’s energy-intensive industries

Model fitting results

According to the STIRPAT extended model established in the “Data and methodology” section, with lnCEP as the dependent variable, and lnCE, lnEI, lnIS, lnGP, (lnGP)², and lnPCA as the independent variables, regression fitting is performed. The fitting results of the coefficients of various variables of the CEP in energy-intensive industries are shown in Table 5.
The formulas fitted to the above table were the functional relationship between the CEP of the six energy-intensive industries in China and the five driving factors of carbon CE, EI, IS, GP, and PCA. As shown in Table 5, all coefficients were significant, and the fitting equation had the high R-square coefficient (>0.9). In order to further verify the validity of the model, the error of the model needed to be tested (Frias-Paredes et al. 2018). Substituting the data on CE, EI, IS, GP, PCA from 2001 to 2020 into their respective equations to calculate the simulated values of the CEP of six energy-intensive industries from 2001 to 2020, and compared the simulated value with the actual value, the result is shown in Fig. 5.

According to Fig. 5, the test results showed that the Mean Absolute Error (MAE) (Frias-Paredes et al. 2018) was 0.92%, 1.32%, 2.13%, 3.40%, 0.66%, and 2.25%, respectively. The simulated carbon emission values from 2001 to 2020 were basically consistent with the actual values, indicating that the fitted equation met the practical significance and can further analyze the CEP equilibrium points of China’s six energy-intensive industries.

Analysis of the CEP equilibrium points of China’s energy-intensive industries under simulated scenario

Based on scenario analysis theory, the key driving factors of CEP in energy-intensive industries were taken as the main parameters for the setting of scenario models. The average annual growth rate of each driving factor was determined according to the 14th Five-Year Plan and China’s historical development trend from the 10th Five-Year to the present. Based on the average growth rate of various factor variables from 2001 to 2020, combined with the 14th Five-Year Plan target, set the change rate parameter of each driving factor of the CEP of the six energy-consuming industries. Among them, two variables such as GP and PCA were set with reference to historical fluctuations and relevant research forecasts. The three variables of CE, EI, and IS were set with reference to historical conditions and combined with the expectations of the 14th Five-Year Plan. This article simulated the equilibrium points of the CEP of China’s six energy-intensive industries by constructing scenarios under the low-carbon transition. The historical situation and average annual growth rates of each driving factor of the six energy-intensive industries were shown in Table 6.

Accurately grasping the mid-to-long-term development trend of China’s economy was essential for trend analysis of various factors. Although there was still gap between China’s current economic development situation and the low-carbon scenario, the 14th Five-Year Plan strengthened the control of China’s low-carbon policy and will achieve low-carbon development at a faster speed in the future. This article set a low-carbon development simulation. The historical trends and future development of each factor were as follows:

(1) Regarding the intensity factors CE and EI, since 2001, the energy utilization efficiency of various industries has been steadily improved, which promoted the continuous decline of energy consumption intensity, especially the energy consumption intensity of energy-intensive industries. As energy-intensive industries continue to transform and upgrade, the intensity effect will continue to decline steadily, maintaining the strong inhibitory effect. Considering that the intensity effect under the low-carbon development scenario will be still the main means of carbon emission reduction, this article assumed that CE and EI will continue to decline. The change trend of energy consumption in energy-intensive industries will be determined according to the trend of future production capacity decline under the guidance of policy, by referring to the China Energy Outlook 2030 (Lu et al. 2020). With reference to the “Carbon Peaking Action Plan by 2030” issued by the State Council (State Council of China, 2021), by 2025, energy consumption per unit of GDP will be 13.5% lower than that in 2020, and carbon dioxide emissions per unit of GDP will be 18% lower than that in 2020. And by 2030, carbon dioxide emissions per unit of GDP will drop by more than 65% from 2005. Especially in the power industry, the “14th Five-Year” Energy Plan clearly stated that the proportion of clean energy installed capacity would increase from 41.9% in 2019 to 57.5% in 2025. And the proportion of clean energy would increase significantly and the carbon

![Image](https://via.placeholder.com/150)

| Industry code | Fitting formula | $R^2$ |
|---------------|-----------------|-------|
| Industry1     | $\ln CEP = 0.788 \ln CE + 0.737 \ln EI + 0.672 \ln IS + 0.984 \ln GP + 0.081 (\ln GP)^2 - 3.599 \ln PCA + \epsilon$ | 0.985 |
| Industry2     | $\ln CEP = 0.954 \ln CE + 0.767 \ln EI + 0.758 \ln IS + 1.044 \ln GP + 0.084 (\ln GP)^2 - 4.213 \ln PCA + \epsilon$ | 0.981 |
| Industry3     | $\ln CEP = 1.068 \ln CE + 0.803 \ln EI + 0.776 \ln IS + 1.048 \ln GP + 0.068 (\ln GP)^2 - 4.391 \ln PCA + \epsilon$ | 0.984 |
| Industry4     | $\ln CEP = 1.143 \ln CE + 0.794 \ln EI + 0.907 \ln IS + 1.016 \ln GP + 0.040 (\ln GP)^2 - 4.697 \ln PCA + \epsilon$ | 0.991 |
| Industry5     | $\ln CEP = 0.727 \ln CE + 0.886 \ln EI + 0.930 \ln IS + 0.970 \ln GP + 0.014 (\ln GP)^2 - 5.127 \ln PCA + \epsilon$ | 0.983 |
| Industry6     | $\ln CEP = 1.475 \ln CE + 0.350 \ln EI + 0.136 \ln IS + 0.551 \ln GP + 0.118 (\ln GP)^2 + 0.898 \ln PCA + \epsilon$ | 0.993 |
emission intensity would further decrease. Combining historical trends, the annual average growth rates of CE and EI of each industry were set as shown in Table 6. (2) Regarding the structural factor IS, the weakening effect of the structural effect on the growth of carbon emissions will gradually increase. Since 2001, the structural effect has been weaker than other effects such as GP, CE, and EI. However, in recent years, the country deeply promoted supply-side structural reforms, a large number of industrial policies were introduced (Song and Zhou 2021), the pace of industrial restructuring accelerated and the driving role of structural effects strengthened. As it enters the stage of high-quality development in the future, the capacity and output of energy-intensive industries will become saturated, development will slow down or even shrink, and their proportion will gradually decline, structural effects will gradually highlight the weakening of carbon emissions growth. Combining historical trends, the average annual growth rate of IS of each industry was set as shown in Table 6.
In view of the factor GP, in the future, China’s economy will continue the trend of slowing down since the new normal and gradually enter a phase of medium-speed growth. The COVID-19 epidemic in 2020 led to a downturn in China’s economy (Wang and Su 2020), but with the introduction of a large-scale stimulus plan, it has shown a steady recovery trend (Wang et al. 2021). Economic development is still China’s main goal at this stage. In the coming decades, China’s economy will continue to develop steadily and rapidly. In 2050, China’s GDP will reach RMB 250,253.7 billion, with an average growth rate of 5.95% (Liu and Xiao 2018). With the acceleration of economic development and urbanization, the population growth rate will show a steady downward trend. In 2020, the national population growth rate was 0.53% compared with the average growth rate in 2010 (National Bureau of Statistics 2021), and it will slowly decrease in the future. The growth rate of economic elasticity will be faster than that of population elasticity. Combined with historical trends, the average growth rate of GP was set as shown in Table 6.

After the above analysis, this article comprehensively considered China’s energy, economic, social development, and the development strategy during and after the 14th Five-Year Plan period, and simulated the development trends of various driving factors. Through calculations, the simulation results of time to achieve the equilibrium points of CEP in six energy-intensive industries are shown in Fig. 6.

According to Fig. 6, under the low-carbon development scenario set in this paper, among the six energy-intensive industries, the CEP of industry 3 will reach the equilibrium point firstly in 2046, followed by industry 2, and will reach the equilibrium point in 2049. The CEP of industry 1 and industry 5 will reach equilibrium in 2050 and 2060, respectively. And the CEP of industry 4 and industry 6 reached equilibrium relatively late, in 2055 and 2058, respectively. This is corroborated with the research of Fang et al. (2022a), which found that the peak time of each industry was different, and the power industry was the latest.

### Table 6 Simulation parameters of factor average annual rate under low carbon scenario

| Scene mode parameters | The 10th Five-Year(2001-2005) | The 10th Five-Year(2006-2010) | The 12th Five-Year(2011-2015) | The 13th Five-Year(2016-2020) | After 2020 |
|-----------------------|-------------------------------|-------------------------------|-------------------------------|-------------------------------|------------|
| Emission intensity    | CE1 -3.81%                    | -2.26%                        | -2.75%                        | -1.19%                        | -1.44%     |
|                       | CE2 -0.81%                    | -3.83%                        | -3.63%                        | -9.16%                        | -1.43%     |
|                       | CE3 -2.18%                    | -1.12%                        | 2.66%                         | -2.62%                        | -0.16%     |
|                       | CE4 -2.31%                    | -0.46%                        | 1.69%                         | 1.66%                         | -2.67%     |
|                       | CE5 -1.33%                    | -6.10%                        | -8.14%                        | -5.22%                        | -3.26%     |
|                       | CE6 4.71%                     | 2.53%                         | -0.91%                        | 0.75%                         | -3.44%     |
| Energy consumption intensity | EI1 3.00%                  | -2.78%                        | 2.76%                         | 5.71%                         | -0.28%     |
|                       | EI2 2.60%                     | -7.15%                        | -4.90%                        | -1.72%                        | -1.14%     |
|                       | EI3 7.77%                     | -8.22%                        | -8.89%                        | -3.56%                        | -3.72%     |
|                       | EI4 -1.77%                    | -3.10%                        | -6.53%                        | -3.17%                        | -3.27%     |
|                       | EI5 -3.05%                    | -5.85%                        | -7.09%                        | 3.15%                         | -3.48%     |
|                       | EI6 0.43%                     | -6.72%                        | -1.04%                        | 3.31%                         | -1.44%     |
| Industrial structure  | IS1 -3.00%                    | -2.81%                        | -0.13%                        | -5.17%                        | -2.53%     |
|                       | IS2 1.92%                     | 2.30%                         | 6.40%                         | -1.09%                        | -1.98%     |
|                       | IS3 -2.28%                    | 4.50%                         | 4.97%                         | -2.16%                        | -1.25%     |
|                       | IS4 12.05%                    | -1.47%                        | 2.97%                         | -1.43%                        | -1.24%     |
|                       | IS5 6.98%                     | 2.68%                         | 15.60%                        | -1.30%                        | -0.19%     |
|                       | IS6 -4.19%                    | -2.50%                        | -1.22%                        | -4.96%                        | -2.57%     |
| Economic scale        | GP 15.17%                     | 19.43%                        | 4.36%                         | 6.45%                         | 12.35%     |
| Carbon sequestration scale | PCA 0.26%                  | -0.20%                        | 0.63%                         | 0.08%                         | 0.46%     |

(3) In view of the factor GP, in the future, China’s economy will continue the trend of slowing down since the new normal and gradually enter a phase of medium-speed growth. The COVID-19 epidemic in 2020 led to a downturn in China’s economy (Wang and Su 2020), but with the introduction of a large-scale stimulus plan, it has shown a steady recovery trend (Wang et al. 2021). Economic development is still China’s main goal at this stage. In the coming decades, China’s economy will continue to develop steadily and rapidly. In 2050, China’s GDP will reach RMB 250,253.7 billion, with an average growth rate of 5.95% (Liu and Xiao 2018). With the acceleration of economic development and urbanization, the population growth rate will show a steady downward trend. In 2020, the national population growth rate was 0.53% compared with the average growth rate in 2010 (National Bureau of Statistics 2021), and it will slowly decrease in the future. The growth rate of economic elasticity will be faster than that of population elasticity. Combined with historical trends, the average growth rate of GP was set as shown in Table 6.

(4) Regarding the factor PCA, the forest stock volume basically remained stable from 2001 to 2020. With the proposal of the carbon peaking and carbon neutrality goals, the role of forests and grassland in carbon sequestration has gradually been paid attention. The Carbon Peaking Action Plan by 2030 proposed (State Council of China, 2021) that by 2030, the national forest coverage rate will reach about 25%, and the forest stock volume will reach 19 billion cubic meters. Therefore, under the low-carbon development scenario, the scale of carbon sequestration will gradually increase, and the average annual growth rate is shown in Table 6.
In-depth comparison found that the time to achieve the equilibrium points of CEP in the six energy-intensive industries showed significant gradient characteristics. The first gradient included industry 2 and industry 3, which were characterized by “single peak” in historical fluctuations. During 2001–2020, their CEP gradually evolved, and then already begun to decline. In addition, the inhibitory effects of CE and EI will be enhanced, the slowdown of GP growth rate will lead to a decrease in the positive driving effect, and IS and PCA will play a certain inhibitory role in the future. In the above situation, the two industries would reach the equilibrium points relatively early. The second gradient were industry 1 and industry 5, which were characterized by the evolution of historical fluctuations as “steady growth.” Between 2001 and 2020, their CEP gradually increased and evolved and is currently basically in a state of stable fluctuations, and will enter a decline stage. In the same way, under the effect of the five factors, the equilibrium would be gradually achieved. The third gradient included industry 4 and industry 6, which were characterized by the evolution of historical fluctuations as “two-stage growth.” From 2001 to 2020, their CEP experienced two stages of growth, and it is still in the growth stage and will not decline in the short term. Driven by the five factors in the three aspects of scale, intensity, and structure, the equilibrium would be finally achieved.

Conclusions and policy implications

Conclusions

As the main industries of energy consumption and carbon emissions, energy-intensive industries had huge pressure to reduce emissions and were particularly important for achieving the carbon peaking and carbon neutrality goals. Based on the factor-driven perspective, this paper studied the dynamic evolution analysis of the equilibrium points of CEP in China’s energy-intensive industries. First, set the definition of the CEP of the six energy-intensive industries then calculated and analyzed the fluctuation and evolution characteristics of the CEP among six industries. The KAYA and LMDI methods were used to decompose the driving factors of the CEP of the six energy-intensive industries into emission intensity (CE), energy consumption intensity (EI), industrial structure (IS), economic scale (GP), and carbon sequestration scale (PCA) from three aspects: scale, intensity, and structure. Based on the historical evolution characteristics of the CEP, combined with the impact of driving factors and the future development of each factor, the simulated low-carbon scenario was set to analyze their equilibrium points through the STIRPAT and EKC comprehensive models. The following conclusions were obtained:

Fig. 6 The simulation results of time to achieve the equilibrium points of CEP in six energy-intensive industries

| Year: 20XX |
|------------|
| industry1  |
| industry2  |
| industry3  |
| industry4  |
| industry5  |
| industry6  |

- Year of Carbon Neutrality Commitment
- Simulation value
- Year of Carbon Peaking Commitment
- Achieved
- Not achieved
(1) By analyzing the fluctuation and evolution characteristics of the CEP of the six energy-intensive industries from 2001 to 2020, it was found that the overall CEP showed a trend of high-speed growth firstly and then steadily fluctuating with 2013 as the boundary. In terms of different industries, the CEP trends of China’s six energy-intensive industries from 2001 to 2020 were basically dissimilated into three types of “two-stage growth” (industry 4, industry 6) and “steady growth” (industry 1, industry 5) and “single peak” (industry 2, industry 3).

(2) Analyzing the driving effect of factors found that there were differences in the effects of five factors from three aspects: scale, intensity, and structure. Among the scale factors, the positive contribution of GP was the largest, while the negative contribution of PCA was small (basically lower than 10%). And there was no significant difference in the degree of influence of the two factors on the six industries. Among the intensity factors, both CE and EI mainly exerted the restraining effect, and EI showed a negative driving effect after 2005, which was the main factor that promoted the reduction of the industries’ CEP. Among the structural factors, the driving directions of the IS for different industries were quite different. Specifically, industries 1 and 6 were mainly affected by the positive driving effects of the IS before 2005, and they were mainly affected by the negative driving effects after 2005, while industries 2, 3, 4, and 5 were the opposite.

(3) By setting the low-carbon scenario for simulation analysis, it was found that the time to achieve the equilibrium points of CEP in the six energy-intensive industries exhibited significant gradient characteristics. The first gradation were the “single peak” industries of industry 2 and 3, which have already begun to decline. Under the influence of the factors, the equilibrium points will be reached relatively early in the future. The second gradient were the “steady growth” industries of industry 1 and 5, which were currently basically in a state of steady fluctuations and will enter a decline phase. Driven by the factors, the equilibrium points were gradually achieved. The third gradient were the “two-stage growth” industries of industry 4 and 6, whose CEP had experienced two stages of growth. The CEP will be still in the growth stage and will not decline in the short term. Driven by the five factors, the equilibrium points can be achieved relatively late.

Policy implications

According to the above conclusions, this paper proposed some practical policy implications to provide reference for China to achieve the carbon peaking and carbon neutrality goals. Some policy implications were as follows:

(1) Although the six energy-intensive industries have the same characteristics of high energy consumption and high carbon emissions, their development was inconsistent. The equilibrium time of the CEP of the six energy-intensive industries showed significant gradient, and corresponding policies need to be formulated according to categories.

(2) China should pay attention to preventing the rebound of carbon intensity after COVID-19, which is consistent with Wang et al. (2021). In the process of stimulating economic recovery, reduce emission intensity as much as possible by strengthening technological innovation.

(3) In the process of realizing the carbon peaking and carbon neutrality goals, the government should not only pay attention to the source of carbon emissions, but also pay attention to the carbon sinks, and should take measures from two perspectives to help the realization of the goals.

This study drew on the concept of regional carbon pressure, fully considered the impact of carbon sinks on industrial carbon emissions, innovatively defined the concept of CEP in energy-intensive industries, and calculated and analyzed the fluctuation evolution characteristics. We innovatively proposed the factor of “carbon sequestration scale” to decompose the driving factors of the CEP from the three aspects of scale, intensity and structure by the KAYA and LMDI methods. Through the STIRPAT and EKC comprehensive model and simulation scenarios, we analyzed the equilibrium points of CEP and found that the time of the equilibrium points in six industries presented a three-level gradient characteristic. For different gradient industries, it was recommended to adopt different preferences for policy implementation, which can provide the reference for the country to formulate suitable and effective emission reduction policies for energy-intensive industries. However, in this paper, limited by data sources, we used forests and grasslands with huge carbon sinks to represent ecological carbon sinks, ignoring the impact of the contributors (agricultural systems) of carbon sink growth. In the future, we will make further comprehensive and in-depth research on the basis of this paper, and strengthen the research on the role of carbon sinks to put forward more targeted suggestions.

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Author contribution

All authors contributed to the study conception and design. Material preparation, data collection, and analysis were performed by Jinpeng Liu and Delin Wei. The first draft of the manuscript was written by Jinpeng Liu and Delin Wei, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.
Availability of data and materials All data generated or analyzed during this study are included in this published article.

Declarations

Ethical approval Not applicable. The manuscript is in compliance with Ethical Standards without any data collected from human subjects.

Consent to participate Not applicable.

Consent to publish The manuscript is approved by all authors for publication, and the work described was original research that has not been published previously, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

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