



Multi-factor decomposition and multi-scenario prediction decoupling analysis of China's carbon emission under dual carbon goal

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HIGHLIGHTS

- Provided a comprehensive multi-factor decompose solution of China's carbon emission.
- Quantified the contribution of different factors and constructed a comprehensive evaluation model to assess different power generation modes.
- Established and verified a system dynamics model for carbon emission prediction.
- Predict and Analyzed relationship between carbon emission and GDP, HDI by decoupling theory.

GRAPHICAL ABSTRACT



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ABSTRACT

Comprehensively clarifying China's carbon emission factors and formulating effective strategies are essential and significant for achieving the "30–60" dual carbon target. This manuscript proposed a novel hierarchical framework of multi-factor decomposition, comprehensive evaluation, prediction, and decoupling analysis of the carbon emission. The multi-factor decomposition model from the perspectives of energy, economy, and society based on the expanding the Kaya Identity and LMDI decomposition method can provide the quantification results. On this basis, this manuscript applies the entropy weight method to construct the evaluation system and generate the index from the environment, energy, and economy dimensions for China's six power generation modes. Furthermore, the carbon emission dynamics model is built based on the carbon emission data in the past 40 years and used to predict China's carbon emission in the next 40 years under multi scenarios combined with Tapio's decoupling theory. The results show that income per capita and thermal power generation result in carbon emission, while energy price and intensity are decreasing. Moreover, reducing energy consumption and increasing the proportion of renewable energy are effective ways to make China's carbon emission peak in 2030, with a peak value of 12.276 billion tons. Eventually, with policies implemented, carbon emission, economic growth, and social development are predicted to reach a strong decoupling state, indicating long-lasting negative correlations. In summary, this study will provide a comprehensive analytical solution for factor decomposition, integrated assessment, and predictive decoupling of carbon emission from a national level, aiming to provide scientifically reasonable suggestions for policies and regulations for the "dual carbon" goal.

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Nomenclatures

C_{ij}	total carbon emission, 10^8 ton
ΔC_{total}	change amount of total carbon emission, 10^8 ton
C^0	carbon emission in the base year, 10^8 ton
C^T	carbon emission in post T-period from the beginning of the base year, 10^8 ton
e_j	entropy value of the j-th evaluation index, no unit
EG	total energy production, 10^4 ton of standard coal equivalent (or "tce" in short)
EC	residential energy consumption, 10^4 tce
$EN_{str,j}$	energy structure effect
$EN_{int,i}$	energy intensity effect
EN_{thr}	thermal power generation ratio
EN_{con}	level of residential energy consumption
$EM_{str,i}$	industry structure effect
EM_{thr}	thermal power output effect
EM_{pri}	energy price effect
GDP_i	Gross Domestic Product, 10^8 RMB
HDI	Human Development Index
IEC_{ij}	industrial fossil energy consumption, 10^4 tce
INC	gross national income, 10^8 RMB
m_j	consumption of the j th fossil energy, 10^4 ton (or 10^8 m ³)
POP	total population, 10^4 people
s_j	the comprehensive score of the j th subject
$S_{car,ij}$	carbon emission factor effect
S_{inc}	level of income per capita, 10^4 RMB/people
S_{urb}	level of urbanization rate
S_{ife}	living scale effect
TEG	amount of thermal power generation, 10^8 kWh
URB	area of urban, km ²
x_{ij}	evaluation index value
$\bar{x}_{ij}$	standardized value of x_{ij}
y_{ij}	proportion of the i th subject index value under the j th evaluation index
Δ	variation of the variables; or representing the sum
ϵ	decoupling elasticity
λ	carbon emission coefficient of different fossil energy, kgCO ₂ /kg (or kgCO ₂ /m ³)
ρ	relative contribution of factors
ω_j	weight of the j th evaluation index

1. Introduction

1.1. Research background and literature review

Environmental protection has been catching worldwide concerns with the increasing exploitation of resources and the harsh consequences of global warming in the fast-developing world. In 2019, the top six countries and regions in the world for CO₂ emissions are China (9.826 billion tons), the United States (4.965 billion tons), the European Union (4.111 billion tons), India (2.48 billion tons), Russia (1.533 billion tons) and Japan (1.123 billion tons) (Liu et al., 2021b). As the largest carbon emitter, China has adopted many policies, measures, and actions to promote green development and set forth the carbon peak and carbon neutralization, i.e., the "dual carbon" goal by 2030 and 2060, as one of the essential national strategies (Peng et al., 2021; Zhang et al., 2021), despite the difficulties this creates for its own economic and social development. The Chinese policymakers are rolling out innovative policies to ensure steady economic growth and achieve dual carbon goals conforming to the actual carbon emission conditions. However, China's carbon emission composition and influencing factors are complex and changeable with multi-subject, multi-

level, and multi-industry characteristics. Therefore, a full grasp of the composition's structure and characteristics and the corresponding assessment of the influencing factors and policy forecasting are crucial in achieving eco-environmental progress and high-quality development.

Many factors can influence carbon emissions in human production and daily life, such as economic growth, energy structure, energy intensity, industrial structure, and population distribution (Cao et al., 2019; Chen et al., 2018; Wang et al., 2018). However, scholars hold different views on the influencing factors of carbon dioxide emissions, and the decomposition analysis methods of the influencing factors are also diverse (Wang and Zhang, 2021). For example, Liu et al. (Chen and Liu, 2004) proved that the Environmental Kuznets Curve (EKC) (Grossman and Krueger, 1991) is applicable to analyze the relationship between carbon emission and economic growth in China. However, the EKC method considers too few factors and fails to predict the various situations in the future (Lin and Jiang, 2009). For a more comprehensive analysis, Lin et al. (Lin and Jiang, 2009) combined the identity proposed by Yoichi Kaya (Kaya, 1989) with the LMDI method proposed by Ang B. W. (Ang, 2005) in their study and showed that the high energy demand and the coal-based energy consumption structure are the primary motivators of China's carbon emission growth. Based on the extended Kaya Identity and LMDI method, numerous subsequent studies are developed at national, provincial, and industry levels, as shown in Table 1. For example, Zhang (Zhang, 2019) revealed that the economic effect is the positive driving factor of carbon emission, followed by the population and energy structure effect based on China's carbon emission data from 2000 to 2015. Meanwhile, some researches about decompose factors of carbon emission have been developed from logistics, transportation, and power industries by LMDI method. Besides, such machine learning methods as artificial neural network (Xu et al., 2019) and discrete grey model (Ding et al., 2020) are also proposed to analyze the influence factors of carbon emission from the national level.

Furthermore, the quantitative and comprehensive evaluation of different influencing factors is needed for carbon emission policymaking. Wherein energy structure and energy intensity, as the main factors affecting China's carbon emissions, are critically reflected in the current electricity production. Analyzing and evaluating China's electricity production methods are essential for formulating policies to transform the energy structure. Recently, various assessing and evaluating methods of power generation have been proposed from different perspectives (Zhang et al., 2018), such as the AHP-Entropy Method (Duan et al., 2016), the anti-Entropy weighting method (Zhao et al., 2022a), and the entropy weight method (Zhou et al., 2013). Li et al. (Li et al., 2018) constructed a provincial assessment framework of carbon emission driving factors using system dynamics modeling. Ma et al. (Ma et al., 2019) provided a household scale-based assessment for the carbon emission factors in the residential building sector. Xu (Xu, 2021) evaluated the development of China's green economy with indexes including driving force, pressure, and state, showing that high consumption of coal is the restricting factor, which calls for the formulation of appropriate policies for the transformation of thermal power. Yu et al. developed a comprehensive evaluation system for the development and utilization of renewable energy from five aspects by using an analytic network process (Yu et al., 2019).

According to the decomposition and evaluation results, many researchers also have put their efforts into the predicting methods for carbon emission based on the related formulating policies, such as the Monte Carlo method (Wang et al., 2019a), grey relational analysis method (Huang et al., 2019; Wang and Ye, 2017), system dynamic method (Sun et al., 2021), and scenario analysis method (Li et al., 2020; Zhao et al., 2022b). For example, Li et al. (Li et al., 2020) developed the factorization and peak prediction using the generalized dividing index method and the scenario analysis method about the carbon emissions from the construction industry, respectively. Zhao et al. (Zhao et al., 2022b) applied the STIRPAT model to investigate the trajectories and peaking time of the household carbon emission in 30 provinces of China by combining three scenarios. Du et al. (Du et al., 2019) introduced the system dynamic method to estimate the carbon emission and intensity of China's construction industry. They investigated the

Table 1
Relative studies about carbon emission in China.

References	Method	Subject	Period	Perspective
(Gu et al., 2019)	LMDI decomposition and system dynamics	Shanghai City	1995–2016	Decompose factors that influence carbon emission in China
(Quan et al., 2020)	LMDI decomposition	China's logistics industry	2000–2016	
(Liu et al., 2021a)		China's transportation industry	2001–2018	
(Wang et al., 2019b)		China's power industry	2003–2016	
(Zhang, 2019)	Kaya Identity and LMDI decomposition	China	2000–2015	Establish an evaluation model then carrying out the assessment
(Wu et al., 2019)			2001–2015	
(Xie et al., 2020)	Accumulated grey model		2016–2025	
(Xu et al., 2019)	Artificial neural network		1978–2050	
(Ding et al., 2020)	Discrete grey model		2000–2020	
(Hou et al., 2021)	IEW-CM		2016	
(Xu, 2021)	EWM	China's green economy development	2008–2019	
(Zhao et al., 2020)	Input-output analysis and EWM	41 industries and sectors in China	2020	
(Yu, 2021)	Tapio's decoupling theory	China's power industry	2000–2030	
(Wang et al., 2019a)	Monte Carlo method	China	2020–2040	
(Sun et al., 2021)	System dynamic		2005–2020	Prediction of China's carbon emission
(Li et al., 2020)	Scenario analysis		2018–2045	

carbon emission scenarios under various economic and technological conditions. These existing studies on China's carbon emissions have focused on carbon emission prediction from various levels such as national, regional, provincial, and household levels and in different industries. Given the carbon emission prediction results, the decoupling effect of carbon emission with economic and social development has also attracted the attention of many scholars based on Tapio's (Tapio, 2005) decoupling theory. For example, Da et al. (Zhang and Da, 2015) found that the increase in energy intensity and non-fossil energy consumption can promote the decoupling of carbon emission and economic growth using data from 1996 to 2010 in China. Yu (Yu, 2021) researched the carbon emission of China's power industry and found that reducing the proportion of fossil fuels in power generation can make the decoupling effect of carbon emission and economic growth more significant.

In conclusion, China currently has the highest annual carbon emissions globally, and a comprehensive and systematic study of China's carbon emissions is of great significance. According to the above literature summary, under the dual carbon strategy, the existing studies on China's carbon emissions mainly focus on decomposing carbon emission factors, comprehensive evaluation, and prediction. Table 1 summarizes the research concerning China's carbon emissions on various subjects in the last three years. These studies found that a multi-level and multi-category factor decomposition of carbon emissions and the comprehensive evaluation of different factors from multiple perspectives are the basis for formulating efficient carbon reduction policies. The prediction methods based on scenario analysis and system dynamics can evaluate the impact of various policies on the period to realize carbon peaking and the resulting carbon emissions, thus providing feasible carbon-neutral pathways in China. It is also desired and necessary to continue comprehensively exploring the impacts of various factors and policies on Carbon emissions (Chen et al., 2018).

1.2. Research contents

Current research on carbon emissions in China focuses on the decomposition of influencing factors and scenario prediction analysis from multi-industry, multi-level, and multi-factor perspectives. On the one hand, it focuses on different industries, such as transportation, construction, iron and steel, energy, etc. On the other hand, it analyzes each industry's carbon emission influencing factors and formulates corresponding carbon reduction measures. Moreover, it mainly focuses on analyzing carbon emission factors in specific regions, such as North China, East China, Northeast China, and other different regions and provinces in China. Furthermore, it predicts the carbon emission under different scenarios in each provincial-level region based on historical carbon emission data analysis. As can be seen, these studies explain the influencing factors of China's carbon emissions more from a local perspective and make corresponding suggestions.

However, there is still a need to deconstruct and quantify carbon emission factors at the national level from a more comprehensive perspective, including energy, economy, and society. Meanwhile, as the essential producer of China's carbon emissions, the energy and power industries still lack structural assessments of various power production modes from the perspective of carbon emissions. In addition, for future carbon emission predictions under different scenarios, there is an urgent need to evaluate various carbon emission reduction policies by quantifying their impact on people's lives and social development.

Therefore, this manuscript focuses on China's carbon emissions and proposes the systemic research route of “factor decomposition, comprehensive evaluation, prediction, and decoupling analysis” to conduct our research shown in Fig. 1. This manuscript combines the extended Kaya Identity with the LMDI method to decompose factors that influence carbon emission from the holistic perspective of energy, economy, and society and quantify the contribution value of each factor. Based on the decomposition factors and results, a comprehensive evaluation model is established to assess the advantages and drawbacks of China's current power generation modes using the Entropy Weight Method. Furthermore, this manuscript develops a system dynamics model of carbon emission to predict China's carbon emission in the future 40 years under five different scenarios, consequently serving as a reference to better formulate policies in achieving the “dual carbon” goal. Additionally, to quantitate the impacts different policies would cause on people's living and social development, we apply Tapio's theory to analyze the decoupling states between carbon emission and GDP, HDI.

2. Modeling and analysis methodologies

2.1. Decomposition model using extended Kaya Identity and LMDI

According to the Kaya Identity, the relationship between carbon emission and social economy, population, resource, and environment factors can be constructed and expressed below

$$CO_2 = \frac{CO_2}{PE} \cdot \frac{PE}{GDP} \cdot \frac{GDP}{POP} \cdot POP \quad (1)$$

where CO_2 , PE, GDP, and POP represent CO_2 emissions, total primary energy consumption, gross domestic production, and total population, respectively.

As the country with the largest carbon emission in the world, China needs to analyze carbon emission from a comprehensive and deep perspective and fully understand the multiple factors that affect carbon emission (Ding et al., 2021). In terms of energy, China's current thermal power generation dominates power generation by about 70 %. Although the installed capacity of new energy is increasing and China has proposed to build a new power system, the proportion of new energy in power generation is still

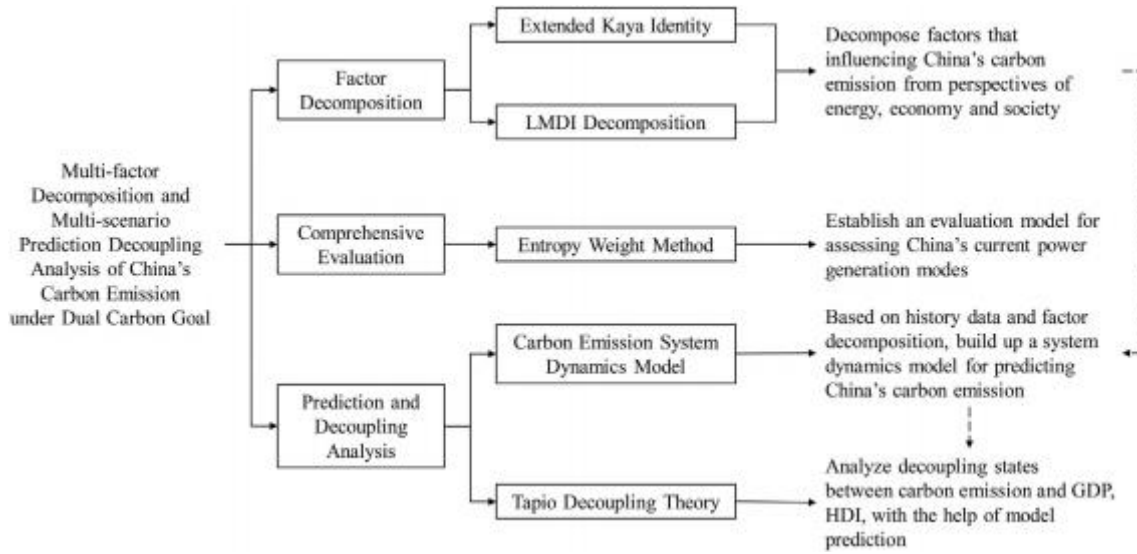


Fig. 1. Schematic diagram of the research framework.

relatively small. In terms of economy, China's total GDP ranks second globally, and it had fully lifted out of poverty by 2020. Besides, the income level and energy consumption per capita are rising. Regarding society, China is one of the world's most populous countries with vast territory. In addition, as the largest developing country globally, China's level of urbanization and human development index keeps growing. Therefore, China's carbon emission factor decomposition should depend on China's national conditions and adapt to local conditions. Based on the above analysis, Fig. 2 illustrates a four-steps flow diagram to explain the factor decomposition solution. The first step is to select 11 different factors from the perspectives of energy, economy, and society. The factors include energy structure, energy intensity, thermal power generation ratio, level of residential energy consumption from the perspective of energy, industry structure, thermal power

output effect, energy price from the perspective of economy, and carbon emission factor, level of income per capita, level of urbanization, and living scale effect from the perspective of society.

Based on the 11 different factors under the above three perspectives, we establish the extended Kaya Identity expressed in Eq. (2). Table 2 shows the meaning of each variable in Eq. (2).

$$\begin{aligned}
 C &= \sum_i \sum_j \left(\frac{C_{ij}}{IEC_{ij}} \cdot \frac{IEC_{ij}}{IEC_i} \cdot \frac{IEC_i}{GDP_i} \cdot \frac{GDP_i}{GDP} \cdot \frac{GDP}{TEG} \cdot \frac{TEG}{EG} \cdot \frac{EG}{EC} \cdot \frac{EC}{INC} \cdot \frac{INC}{POP} \cdot \frac{POP}{URB} \cdot URB \right) \\
 &= \sum_i \sum_j (S_{car,ij} \cdot EN_{str,ij} \cdot EN_{int,i} \cdot EM_{str,i} \cdot EM_{thr} \cdot EN_{thr} \cdot EN_{con} \cdot EM_{pri} \cdot S_{inc} \cdot S_{urb} \cdot S_{life})
 \end{aligned} \quad (2)$$

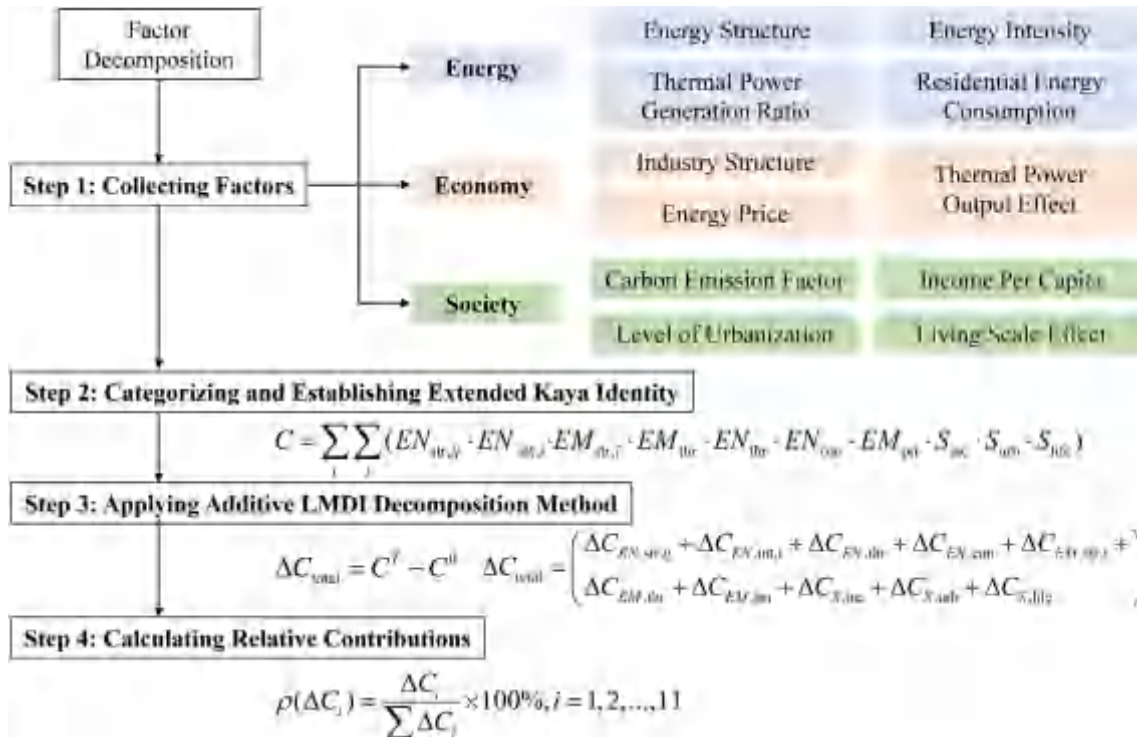


Fig. 2. Factor decomposition flow diagram.

Table 2

Classification and explanation of variables in extended Kaya Identity.

Symbol	Explanation	Symbol	Explanation
Energy	$EN_{str,ij} = IEC_{ij}/IEC_i$	IEC_{ij}	Industrial fossil energy consumption, using i, j to distinguish the consumption of the j-th fossil energy in the i-th industry, where i = 1, 2, 3 respectively represents the primary, secondary and tertiary industries; j = 1, 2, 3 respectively represents coal, oil and natural gas
	$EN_{int,i} = IEC_i/GDP_i$	GDP_i	Gross Domestic Product, use i to represent the output value of different industries. Without subscript, it represents China's GDP in that year
	$EN_{thr} = TEG/EG$	TEG	The amount of thermal power generation
	$EN_{con} = EG/EC$	EG	Total energy production
	$EM_{str,i} = GDP_i/GDP$	EC	Residential energy consumption
	$EM_{thr} = GDP/TEG$	INC	Gross national income
	$EM_{pri} = EC/INC$	C_{ij}	Total carbon emission, which refers to the carbon amount corresponding to the heat released by fossil energy combustion (mainly coal, oil and natural gas). Using i, j to distinguish the carbon emission of the j-th fossil energy in the i-th industry
Economy	$S_{car,ij} = C_{ij}/IEC_{ij}$	POP	Total population
	$S_{inc} = INC/POP$	URB	Area of urban, which can be applied to measure the living scale of Chinese people
Society	$S_{urb} = POP/URB$		
	$S_{life} = URB$		

In Table 2, the following equation can be used for calculating carbon emission,

$$C_j = \lambda_j \cdot m_j; j = 1, 2, 3 \quad (3)$$

where C_j is the carbon emission of the j^{th} fossil energy, $j = 1, 2, 3$ represents coal, oil, and natural gas, respectively. λ_j is the carbon emission coefficient of different fossil energy, selected from the discount standard coal coefficient recognized in the China Energy Statistical Yearbook and shown in Table 3. m_j is the consumption of the j^{th} fossil energy. The energy consumption, power generation, population, and GDP data in Table 2 are derived from the "National Energy Balance Table" in the China Energy Statistical Yearbook and the results of the China Statistical Yearbook from 1980 to 2020. For the data of missing years, this manuscript uses the spline interpolation method for a rough estimation.

For Eq. (2), since the carbon emission factor of fossil energy is the carbon emission coefficient for that type of energy, and it is generally taken as a constant in practical application, only 10 factors except for $S_{car,ij}$ are used in the actual calculation. Eq. (2) can be rewritten as follows

$$C = \sum_i \sum_j \left(EN_{str,ij} \cdot EN_{int,i} \cdot EM_{str,i} \cdot EM_{thr} \cdot EN_{thr} \cdot EN_{con} \cdot EM_{pri} \cdot S_{inc} \cdot S_{urb} \cdot S_{life} \right) \quad (4)$$

Based on the selected carbon emission factors in China, this manuscript applies the additive decomposition model in the LMDI decomposition method (Ang, 2005) to decompose different factors, namely

$$\Delta C_{total} = C^T - C^0 \quad (5)$$

where ΔC_{total} is the change amount of total carbon emission. C^0 is the carbon emission in the base year, and 1980 is chosen as the base period in

this manuscript. C^T is the carbon emission in post T-period from the beginning of the base year.

Based on the additive decomposition model, Eqs. (6)–(15) decompose and calculate the contributions of the 10 factors in the model expressed in Eq. (4).

$$\Delta C_{EN;str,ij} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EN_{str,ij}^T}{EN_{str,ij}^0} \right) \quad (6)$$

$$\Delta C_{EN;int,ij} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EN_{int,ij}^T}{EN_{int,ij}^0} \right) \quad (7)$$

$$\Delta C_{EN;thr} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EN_{thr}^T}{EN_{thr}^0} \right) \quad (8)$$

$$\Delta C_{EN;con} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EN_{con}^T}{EN_{con}^0} \right) \quad (9)$$

$$\Delta C_{EM;str,i} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EM_{str,i}^T}{EM_{str,i}^0} \right) \quad (10)$$

$$\Delta C_{EM;thr} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EM_{thr}^T}{EM_{thr}^0} \right) \quad (11)$$

$$\Delta C_{EM;pri} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{EM_{pri}^T}{EM_{pri}^0} \right) \quad (12)$$

$$\Delta C_{S;inc} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{S_{inc}^T}{S_{inc}^0} \right) \quad (13)$$

$$\Delta C_{S;urb} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{S_{urb}^T}{S_{urb}^0} \right) \quad (14)$$

$$\Delta C_{S;life} = \sum_i \sum_j \left(\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - \ln C_{ij}^0} \cdot \ln \frac{S_{life}^T}{S_{life}^0} \right) \quad (15)$$

Table 3

Carbon emission coefficient of different fossil energy.

Types of fossil energy	Discount standard coal coefficient (kg tce/kg, m ³)	Standard coal discounted CO ₂ coefficient (kgCO ₂ /kg tce)	Carbon emission coefficient (kgCO ₂ /kg, m ³)
Coal	0.7143	2.6604	1.9003
Oil	1.4286	2.1141	3.0202
Natural gas	1.3300	1.6257	2.1622

Combining Eq. (5), the total carbon emission effect can be obtained (Ang, 2005).

$$\Delta C_{\text{total}} = \left(\frac{\Delta C_{\text{EN};\text{str};ij} + \Delta C_{\text{EN};\text{int};i} + \Delta C_{\text{EN};\text{thr}} + \Delta C_{\text{EN};\text{con}} + \Delta C_{\text{EM};\text{str};i} + \Delta C_{\text{EM};\text{thr}} + \Delta C_{\text{EM};\text{pri}} + \Delta C_{\text{S};\text{inc}} + \Delta C_{\text{S};\text{urb}} + \Delta C_{\text{S};\text{life}}}{\Delta C_{\text{EM};\text{thr}} + \Delta C_{\text{EM};\text{pri}} + \Delta C_{\text{S};\text{inc}} + \Delta C_{\text{S};\text{urb}} + \Delta C_{\text{S};\text{life}}} \right) (16)$$

For clarity, we calculated the relative contribution of each factor according to

$$\rho(\Delta C_i) = \frac{\Delta C_i}{\sum \Delta C_i} \times 100\%, i = 1, 2, \dots, 11 \quad (17)$$

where ΔC_i represents the sum of the contribution of the i^{th} factor from 1980 to 2020. $\sum \Delta C_i$ represents the sum of the contribution of all the factors from 1980 to 2020. If $\rho(\Delta C_i)$ is positive, it suggests that the i^{th} factor may promote the increase of carbon emission, and the greater $\rho(\Delta C_i)$ is, the more significant influence the factor would have. In contrast, if $\rho(\Delta C_i)$ is negative, it infers that the i^{th} factor may inhibit the growth of carbon emission, and the smaller $\rho(\Delta C_i)$ is, the more negative impact the factor would cause.

2.2. Evaluation model based on entropy weight method

A comprehensive deconstruction of the factors influencing China's carbon emissions from energy, economic and social perspectives facilitates policy decisions from different aspects, thus promoting the achievement of China's "dual carbon" goal. As the "main driving force" of energy production, the impact of the power industry on carbon emission cannot be ignored. Therefore, evaluating different power production modes from the carbon emission perspective is essential for formulating relevant carbon emission reduction policies. Among them, it is imperative to select the appropriate evaluation method. By collecting a limited amount of data on the cost, power generation, and installed capacity of six power generation methods, including thermal, hydro, wind, solar, and biomass power from 2001 to 2020, this manuscript finds that the entropy weight method (EWM) is suitable to build an evaluation model of China's power production modes since it is an objective valuation method that depends on the discreteness of the data itself. Entropy measures the disorder degree of the system, and the concept of information entropy derived from information theory shows that the lower the entropy value that a piece of information can provide, the greater the dispersion of that information and the greater the weight of influence on the outcome in the evaluation.

Suppose there are n evaluation subjects and m evaluation indexes, x_{ij} represents the j^{th} evaluation index value of the i^{th} evaluation subject ($i = 1, 2, \dots, n, j = 1, 2, \dots, m$), divided into positive and negative indicators. Fig. 3 illustrates the evaluation process of the EWM. For the positive

indicator, since the higher the value of this indicator, the greater the degree of positive contribution to the system, its standardized treatment is

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (18)$$

The standardized treatment of the negative indicators is

$$x'_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (19)$$

Let y_{ij} represent the proportion of the i^{th} subject index value under the j^{th} evaluation index, namely

$$y_{ij} = x'_{ij} / \sum_{i=1}^n x'_{ij} \quad (20)$$

then the entropy value of the j^{th} evaluation index is

$$e_j = - \frac{1}{\ln n} \sum_{i=1}^n y_{ij} \ln y_{ij} \quad (21)$$

Its weight could be expressed as

$$\omega_j = (1 - e_j) / \sum_{j=1}^m (1 - e_j) \quad (22)$$

Therefore, the overall score for each subject can be calculated by

$$S_i = \sum_{j=1}^m \omega_j x'_{ij} \quad (23)$$

Substituting the collected data into Eqs. (18)–(23) will achieve the evaluation of the power production modes based on the scores.

2.3. Multi-scenario prediction model

The decomposition of China's carbon emission factors and evaluate the current power production modes reflect China's overall carbon emission situation. The different policies developed in the "dual carbon" goal will affect China's carbon emission, economic growth and social development. Therefore, various policy-based multi-scenario predictions and quantitative carbon emission analysis are particularly important to consider the extended impacts of carbon emission. Based on the results of factor decomposition, this section establishes the system dynamics model of China's carbon emission, as displayed in Fig. 4. The main processes of the model are shown as follows.

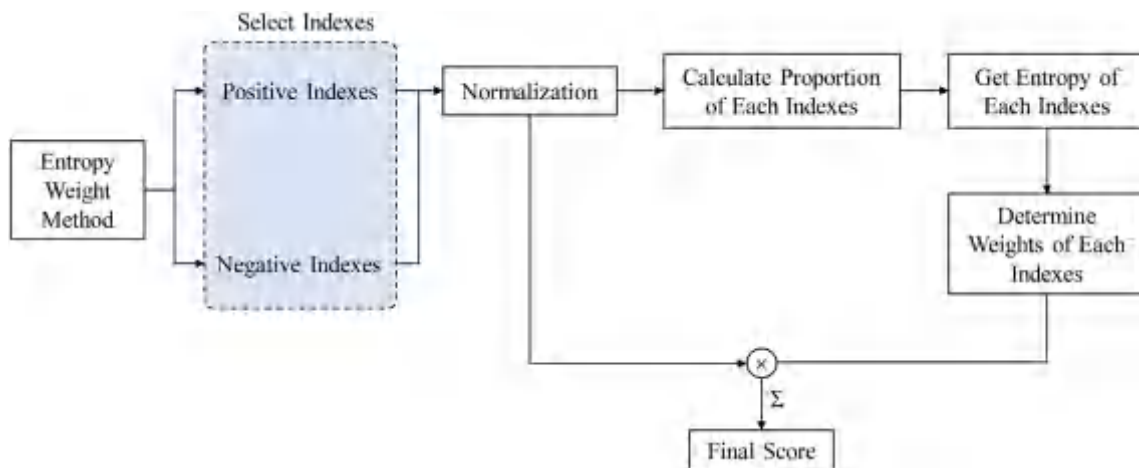


Fig. 3. Evaluation process based on the EWM.

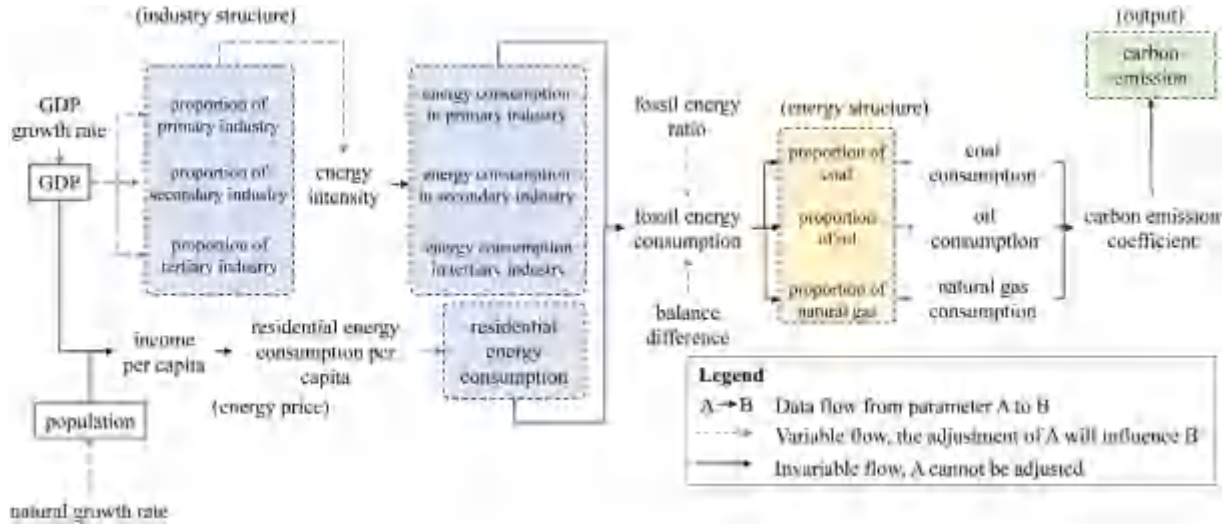


Fig. 4. System dynamics model of China's carbon emission.

The inputs of this system dynamic model are GDP and population. In a given year, the proportion of the output value of three types of industries to the total GDP is called the “industry share,” and the amount of energy consumed per unit of GDP output is called the “energy intensity.” For this purpose, using “industry share” and “energy intensity” can calculate the total energy consumption of the three types of industries for the year. For example, the population and GDP of the year can help calculate the “level of income per capita” of the year and obtain the total amount of living energy consumption according to the level of living energy prices. The total fossil energy consumption in the current year can be obtained by multiplying the total energy consumption of the three types of industries by the proportion of fossil energy, adding the total amount of living energy consumption, and considering the balance difference in the current year due to stockpiles, import, and export, etc. According to the proportion of coal, oil, and natural gas in the three major fossil energy sources and the corresponding carbon emission coefficient, this model outputs the total carbon emission of China in the current year.

By applying the VENSIM software, this manuscript sets up five scenarios based on historical carbon emission data from 1990 to 2020 with a time step of 1 year to project China's carbon emission in the future from 2021 to 2060. Based on the carbon emission system dynamics model, the predicted results can be obtained under different economic and social development scenarios. Therefore, aiming at the prediction of carbon emission, economic and social development in the future, this manuscript introduces the Tapio decoupling model (Tapio, 2005) to analyze the decoupling state between carbon emission and economic development (represented by GDP) and social development (represented by HDI, data taken from the United Nations Development Programme's Human Development Report 2019) from 2021 to 2060.

Table 4 summarizes various types of decoupling and their practical significance (Tapio, 2005), which can be divided into three categories: negative decoupling, decoupling, and coupling. DX/X and DY/Y represent the change rate of variables X and Y with time, which means that $DX/X > 0$ and $DY/Y > 0$ indicate that X and Y increase with time and ϵ is the “decoupling elasticity” defined in Eqs. (24)–(25) below

$$\epsilon(C_{\text{total}}, \text{GDP}) = \frac{\Delta C_{\text{total}}}{C_{\text{total}}} = \frac{\Delta \text{GDP}}{\text{GDP}} \quad (24)$$

$$\epsilon(C_{\text{total}}, \text{HDI}) = \frac{\Delta C_{\text{total}}}{C_{\text{total}}} = \frac{\Delta \text{HDI}}{\text{HDI}} \quad (25)$$

where the symbol “ Δ ” in the equation indicates the change of the variable between this year and the previous year.

3. Results and discussions

3.1. Decomposition of factors

3.1.1. Factors' relative contributions

This manuscript chooses 1980 as the base year, and the LMDI decomposition results can refer to in Appendix Table 1. Fig. 5 presents the results of the relative contribution of each factor to carbon emission. It can be seen that among all the factors, only three have negative values, indicating that they may inhibit the increase of carbon emission. For example, they are energy price (−92.28 %), energy intensity (−75.53 %), and industry structure (−1.57 %) in order, among which the influence of industry structure is relatively minor. The top five factors that have positive values are level of income per capita (116.53 %), thermal power output effect (54.96 %), living scale effect (54.10 %), thermal power generation ratio (28.98 %), and level of urbanization (11.12 %), and influences of the rests are far minor.

3.1.2. Discussions of promoting factors

It can be inferred from Fig. 5 that the relative contribution of the income level per capita may be the primary driver of carbon emission. Some scholars (Wu et al., 2019; Zhang, 2019) also present a similar conclusion since China's economy has grown swiftly and steadily. According to China Statistical Yearbook, income per capita in China in 2020 will be 100,878.25 billion RMB, which is twice than 41,035.41 billion RMB in 2010. Along with the increase of income per capita is the stimulation of domestic demand, which encourages residential energy consumption to increase, promoting carbon emission.

As shown in Fig. 5 the relative contribution of thermal power output effect and thermal power generation ratio is 54.96 % and 28.98 %, respectively, caused by China's major-thermal-based power generation structure. According to China Statistical Yearbook, Fig. 6 demonstrates that thermal power, mainly the coal-fired power generation, accounts for >90 % of carbon emissions in the whole power industry (Ma et al., 2022; Zhang et al., 2021), and it continues to be the primary power generation mode in China from 2001 to 2019. In comparison, the proportion of new energy like wind and solar remains low. Thus, it is still significant to carry on the thermal power transformation and upgrades to a cleaner and more efficient status.

Fig. 5 also shows that the relative contribution of urbanization and living scale effect are 11.12 % and 54.11 %, respectively, which can be attributed to the expansion of the urban area for living and the growing demand for construction and transportation. In comparison, energy structure and residential energy consumption level are weak in promoting carbon

Table 4
Tapio's decoupling states (take carbon emission and economic development as an example).

Types of decoupling		DX/X	DY/Y	$\epsilon(X,Y)$	Explanation
Negative decoupling	Expansive negative decoupling	$DX/X > 0$	$DY/Y > 0$	$\epsilon > 1.2$	Economic growth comes at the cost of increased carbon emission
	Strong negative decoupling	$DX/X > 0$	$DY/Y < 0$	$\epsilon < 0$	Economic recession with increasing carbon emission, the least desirable
	Weak negative decoupling	$DX/X < 0$	$DY/Y < 0$	$0 < \epsilon < 0.8$	Carbon emission is decreasing at a slower rate than the economic downturn
Decoupling	Weak decoupling	$DX/X > 0$	$DY/Y > 0$	$0 < \epsilon < 0.8$	Carbon emission is increasing at a slower rate than economic growth
	Strong decoupling	$DX/X < 0$	$DY/Y > 0$	$\epsilon < 0$	Economic growth with reduced carbon emission, ideal
	Recessive decoupling	$DX/X < 0$	$DY/Y < 0$	$\epsilon > 1.2$	Carbon emission is decreasing faster than the economy declines
Coupling	Expansive coupling	$DX/X > 0$	$DY/Y > 0$	$0.8 < \epsilon < 1.2$	Carbon emission is growing at the same pace as the economy
	Recessive coupling	$DX/X < 0$	$DY/Y < 0$	$0.8 < \epsilon < 1.2$	Carbon emission is declining at the same pace as the economy

emission. Furthermore, the changes in energy structure and residential energy consumption underwent a slow and long evolutionary process. In addition, the selected time section has limited coverage on coal and electrification development, thus failing to illustrate their impacts on carbon emission fully.

3.1.3. Discussions of inhibiting factors

As shown in Fig. 5 energy price and intensity can hinder carbon emission growth, contributing by -92.28% and -75.53% , respectively. According to economics, the rise in the energy price will curb energy consumption. Moreover, a higher energy intensity means less energy is consumed with the increase in GDP and technology development, which can slow down the rise of carbon emissions. Compared with energy price and energy intensity, the contribution of industry structure is -1.57% , hardly restraining the increase of carbon emission. Therefore, the green transformation of industry structure seems beneficial for economic growth and carbon emissions reduction.

3.2. Comprehensive evaluation of six power generation modes

Based on the significant contribution of thermal power generation to carbon emission, the transformation of thermal power generation is essential for carbon reduction. Thus, this manuscript establishes an EWM-based evaluation model to assess different power generation modes in China, focusing on three aspects: energy, environment, and economy.

3.2.1. Comprehensive scores

Table 5 shows the evaluation indexes of different power generation modes using data from previous studies (Gagnon et al., 2002; Wu et al., 2009) and China Power Statistics Yearbook 2021. It should be noted that after substituting into Eqs. (18)–(23), the average of the original scores of the segment indicators is now used as the final score of “environment, energy and economy” for clarity (for example, the final score of the economy

index is the average of the original scores of “fuel cost”, “operation and maintenance cost” and “investment”). The results are converted based on 100. Table 6 lists the final results.

Fig. 7 presents the comprehensive score distribution of thermal, hydro, wind, nuclear, solar, and biomass power generation modes from the environment, energy, and economy indexes, wherein thermal and hydro score relatively high in the energy index, 38.31 and 34.20, respectively. The economy index's top three are hydro, nuclear and thermal, and their scores are 21.99, 20.52, and 18.69, respectively. From the environment perspective, thermal scores 4.07, which is the lowest. Moreover, the biomass scores 10.72, a little higher than thermal. Scores of other power generation modes are all above 20.

3.2.2. Discussions of different power generation modes

The high thermal and hydro power scores from the energy perspective may be attributed to their large installed capacity and high energy efficiency. According to the China National Bureau of Statistics and China Electricity Council, in 2019, thermal power takes up to 70 % of the total installed capacity, reaching 1189.57 million kW. In comparison, hydro power has a relatively small scale in installed capacity and power generation. However, based on Table 5, its energy payback ratio and efficiency are far greater than the others. Therefore, the energy index scores are almost identical between thermal and hydro power. Other power generation modes do not have great installed capacity or power generated, leading to a lower energy index score.

From the perspective of the economy, thermal, hydro, and nuclear power score similarly. In Table 5, hydro power requires a certain cost in the preliminary construction, but the advantage of fuel-cost-free minimizes its total cost. Nuclear power demands a large investment and certain fuel costs, scoring below hydro power. Though the unit cost of thermal power is the least compared to others, fuels like coals are expensive and thus reach a relatively lower score than hydro and nuclear power. New energies like wind and solar power are still in their infancy, with the large scale of

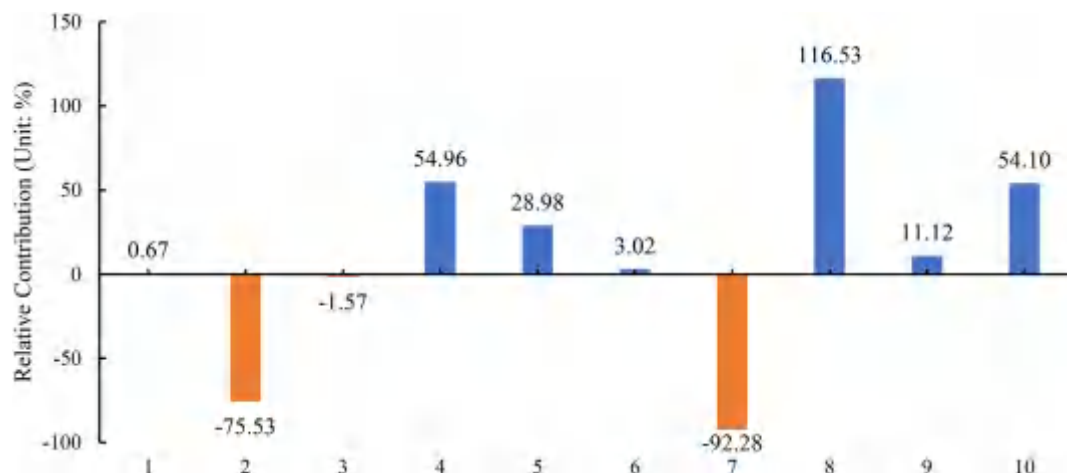


Fig. 5. Relative contribution of carbon emission factors in China from 1981 to 2020. (1-energy structure, 2-energy intensity, 3-industry structure, 4-thermal power output effect, 5-thermal power generation ratio, 6-residential energy consumption level, 7-energy price, 8-income per capita level, 9-urbanization level, 10-living scale effect)

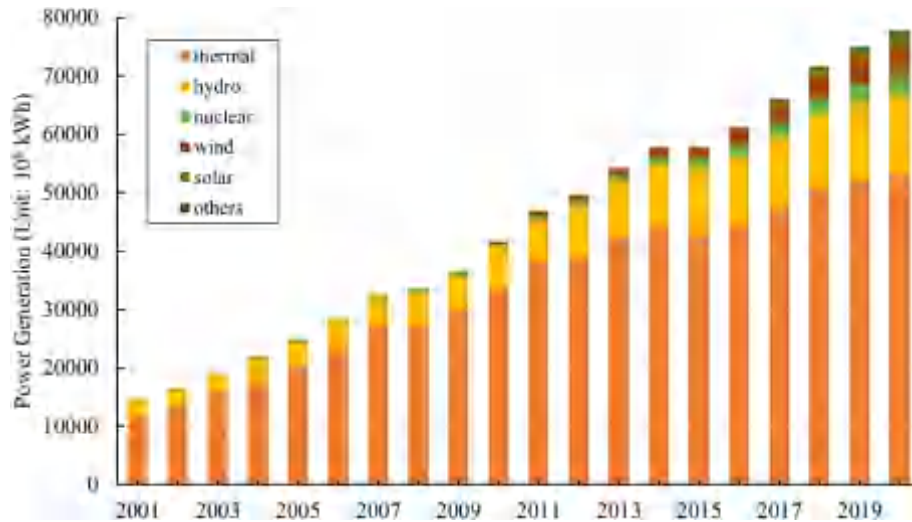


Fig. 6. Power generation of different modes in China from 2001 to 2020.

continued investments of 265.3 billion and 6.25 million RMB in 2020, respectively, according to China Power Statistics Yearbook 2021, and they have not brought considerable economic benefits so far. In 2020, wind power only generated 281.65 million kW, <13 % of that year's total power. Similarly, solar power generates no >12 % of the power that year. The economic benefits of wind, solar, and other new energies have not been realized, and high investments but immature technology and low power generated may be the primary cause.

Thermal power seems to have considerable advantages, but we should not neglect the lowest score it gets in terms of the environment. As LMDI decomposition results are stated in Section 3.1.1, thermal power output and generation ratio are the leading cause of promoting carbon emission.

Thus it is urgent for upgrade and transformation. Biomass scores lower can be possibly ascribed to large-scale land exploitation, especially on forests and farms. In addition, with the unmaturing technology, its power generation efficiency would be further reduced, resulting in a lower environment index score.

In summary, thermal power generation is superior in energy and economy, but it may not be ideal for satisfying the low-carbon development needs. Though new energy is inferior in terms of energy and economy, the potential for technological advancement and environmental protection are promising. In 2021, the Global Wind Energy Council released its report, revealing that China's newly installed onshore and offshore wind power capacity reached 30.7GW and 16.88GW, respectively, ranking first globally.

Table 5
Evaluation indexes of six power generation modes in 2020.

Evaluation indexes		Power generation modes					
		Thermal	Hydro	Wind	Nuclear	Solar	Biomass
Environment	CO ₂ emission(g/kWh)	986	0	0	0	0	58
	SO ₂ emission (g/kWh)	8.56	0	0	0	0	0.076
	NO _x emission (g/kWh)	2.986	0	0	0	0	1.325
	particles emission (g/kWh)	0.347	0	0	0	0	0.269
	land requirement (km ² /TWh)	4	152	72	0.5	45	533
Energy	installed capacity (10 ⁴ kW)	124,517	37,016	28,153	4989	25,343	2254
	power generation (10 ⁸ kWh)	53,302.48	13,552.09	4146	3662.5	1421	1111
	energy payback ratio(%)	7	205	80	16	9	5
	efficiency(%)	39.4	80	35	33.5	9.4	28
	average annual utilization coefficient	67	41	27	86	20	67
Economy	unit cost (RMB/kW)	5347.86	8553.59	8823.22	12,733	33,127.65	13,252.65
	fuel cost (RMB/kWh)	0.104	0	0	0.021	0	0.163
	operation and maintenance cost (RMB/kWh)	0.081	0.057	0.091	0.095	0.196	0.118
	investment (10 ⁸ RMB)	567	1067	2653	379	625	1502

Table 6
Comprehensive score of six power generation modes.

Power generation modes	Original scores			Converted scores		
	Environment	Energy	Economy	Environment	Energy	Economy
Thermal	0.0016	0.0487	0.0076	4.0678	38.3138	18.6913
Hydro	0.0083	0.0435	0.0089	20.6534	34.1959	21.9922
Wind	0.0086	0.0168	0.0065	21.2685	13.1988	16.0649
Nuclear	0.0088	0.0099	0.0083	21.8183	7.7751	20.5180
Solar	0.0087	0.0034	0.0050	21.4762	2.6542	12.2078
Biomass	0.0043	0.0049	0.0043	10.7158	3.8621	10.5258
			Sum	100	100	100

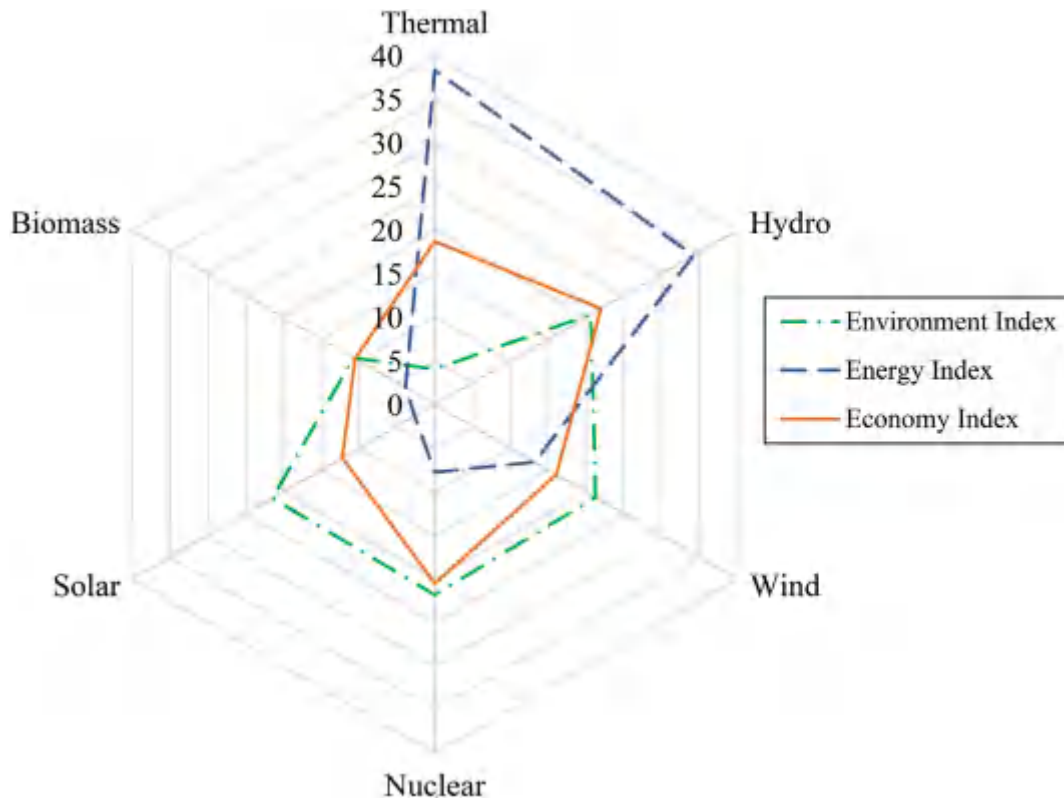


Fig. 7. Comprehensive score distribution of six power generation modes.

In 2022, China's first self-developed 13 MW offshore wind turbine went offline in Fuqing, Fujian Province, with a 30 % increase in rated power compared with the 10 MW offshore direct drive wind power platform into operation in batches with mature technology.

3.3. Prediction and decoupling analysis

Based on the existing data, this manuscript decomposes China's carbon emissions' influencing factors and establishes an evaluation model for the existing power generation modes. This subsection will predict and analyze the decoupling effect based on the carbon emission system dynamics model in the following discussion.

3.3.1. Model verification

Fig. 8 displays China's carbon emission curve based on the system dynamic model simulation and calculation. To verify the reliability of model

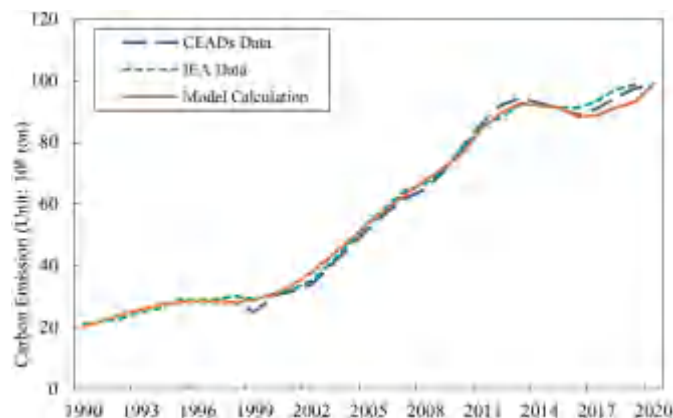


Fig. 8. Comparison of calculated results and the actual data.

results, China's carbon emission data from the CEADs (the year 1997 to 2020) and the IEA (the year 1990 to 2019) are collected for comparison. The results showed that the calculated values of China's carbon emission from 1997 to 2020 have an average error of no >2.14 % in the recent 15 years. Meanwhile, compared with the data provided by IEA from 1990 to 2019, the average error in the recent 15 years is <2.41 %. Therefore, it can be considered that the system dynamics model is feasible and has satisfying accuracy for predicting carbon emission.

3.3.2. Multi-scenarios prediction analysis

The proposed system dynamics model has good accuracy and feasibility for carbon emission prediction. Table 7 lists five typical scenarios for future planning policies based on the relevant news reports in China in the past two years. Scenario 1 is without any adjustment and is named "let it go". Scenario 2 is a decrease in energy consumption of industries and an increase in the share of non-fossil fuels, i.e., "energy consumption decline." Scenario 3 is the annual GDP growth rate continues to decline, and the industrial structure is upgraded from the economic side, i.e., "industry adjustment." Scenario 4 is the orderly increase in per capita residential energy consumption, i.e., "energy demand regulation." Scenario 5 is a combination of scenario 2 and scenario 4, i.e., simultaneous control of energy production and consumption. In the above five scenarios, the proposed system dynamics model is applied to predict China's carbon emissions from 2021 to 2060 and explore the possibility of achieving China's "dual carbon" goal.

Fig. 9 shows these predicted outcomes after model calculation. Except for Scenario 1, all other four scenarios would experience an inverted "U" trend in the following 40 years. However, scenario 1 does not make any adjustments and has a rapid growth in carbon emission. Scenarios 2 to 5 inhibit China's carbon emission to varying degrees, and the difference lies in the peaking time. The carbon emission of Scenarios 3 and 4 will peak in 2047 and 2048, respectively, among which the former has a peak value of 19.568 billion tons and the latter has a lower peak value of 17.677 billion tons. In comparison, Scenario 2 responds more swiftly.

Table 7
Five different scenarios and related features.

Scenarios	Features			Parameters
	Energy	Economy	Society	
Scenario 1 (let it go)	No adjustments			The annual change rate of energy intensity of each industry is -2.70% per year, and the growth rate of non-fossil energy consumption is 0.57% per year. The other variables are the same as Scenario 1 The economic growth rate from 2021 to 2025 and 2026 to 2030 is 5.50% and 4.50% , the proportion of secondary industry in 2020 and 2030 is 37.60% and 30.50% , respectively. The proportion of tertiary industry is 54.70% and 65% respectively. Other variables are the same as Scenario 1 The growth rate of energy intensity of tertiary industry is -0.13% per year, and the growth rate of per capita residential energy consumption is 1.114 tce per year. Other variables are the same as Scenario 1
Scenario 2 (energy consumption decline)	"By 2025, the energy consumption per unit of industry value added above designated size will decrease by 13.50% , and the proportion of non-fossil energy in total energy consumption will reach about 20% ."	×	×	
Scenario 3 (industry adjustment)	×	"The average annual GDP growth rate declines, and the industrial structure continues to upgrade."	×	
Scenario 4 (energy demand regulation)	"The growth of industrial energy demand slowed down, and the energy consumption level of agriculture and construction remained stable. The energy consumption of the tertiary industry increased by nearly 1 billion tons of standard coal, with an average annual growth of 5% ."	×	"Residential energy consumption will exceed 800 million tons of standard coal in 2030, and the per capita residential energy consumption will be close to 600 kg."	
Scenario 5 (combination)	a comprehensive combination of Scenario 2 to 4			

After 2030, carbon emission in Scenario 2 shows a significant declining trend and first reaches the maximum carbon emission of 13.505 billion tons in 2030. Besides, the carbon emission of Scenario 5 also peaks in 2030 with the lowest peak value of 12.276 billion tons. Therefore, it can be concluded that compared with Scenarios 3 and 4, Scenario 2 distinguishes itself in formulating appropriate energy policies. In Scenario 2, energy consumption per industry value-added reduction can be understood as energy efficiency improvement. Increasing the proportion of non-fossil energy is a way to encourage low-carbon development.

Our earliest estimated peak time and peak value of carbon emission are around 2030, which is within the range of predictions previous studies have made. According to some scholars' estimations, China will peak its carbon emission (Fan and Zhang, 2021; Wang et al., 2019a) between 2021 and 2025 optimistically or will peak in 2031 with a 63.12% decrease in carbon emission intensity compared with 2005 (Wang et al., 2020). The latest peak time will be around 2040 (Jiang et al., 2009). In addition, the peak value varies from 8 billion tons (Jiang et al., 2009) to 16 billion tons (Yue et al., 2010).

3.3.3. Decoupling analysis under different scenarios

According to Eq. (24) and Eq. (25), Fig. 10 and Fig. 11 display the decoupling elasticity curves between carbon emission, GDP, and HDI. From 1990 to 2020, the curves of Fig. 10 and Fig. 11 fluctuated violently and went through a state of expansive negative decoupling, expansive coupling, and weak decoupling. Therefore, China still needs to actively promote a green transformation in economic development and social development.

Fig. 10 represents that the curves of five scenarios all decline after 2021. According to Table 8, Scenario 1 shows expansive negative decoupling from 2021 to 2025, indicating that the growth of GDP is at the cost of increased carbon emission to a certain extent. From 2026 to 2030, it has maintained an expansive coupling, indicating that the environmental pressure caused by carbon emission increases at the same pace as economic growth. Scenarios 3 and 4 are similar. The transit from weak decoupling to strong decoupling around 2046 means China has improved energy utilization levels, increased energy efficiency, and decreased consumption per unit GDP. All of that can make the growth rate of carbon emissions lower than economic growth. With the increase in China's GDP, carbon emission

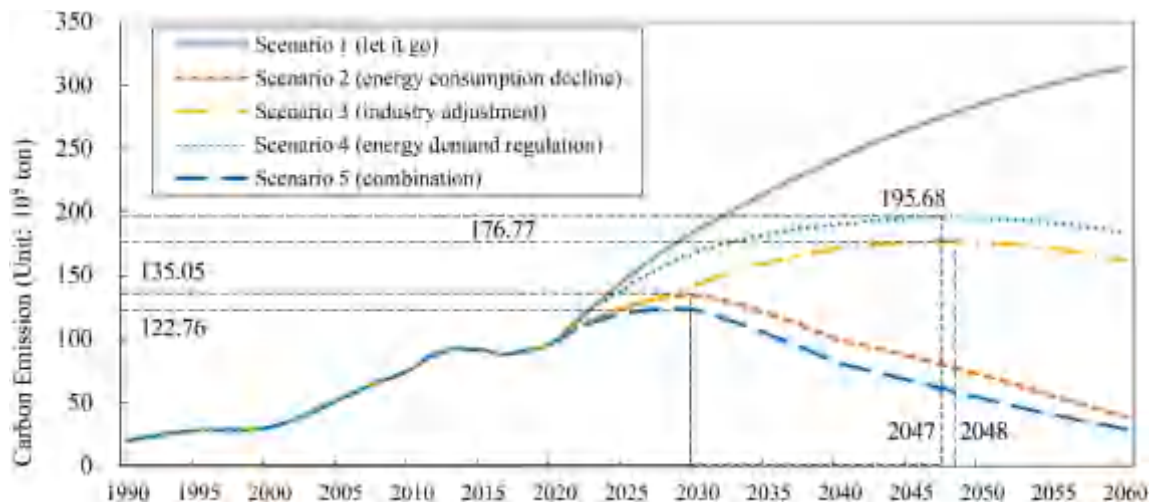


Fig. 9. China's carbon emission under different scenarios.

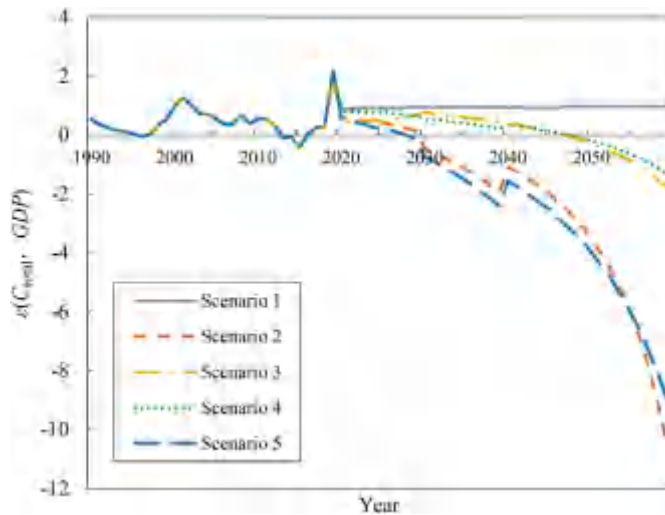


Fig. 10. The decoupling state between carbon emission and GDP.

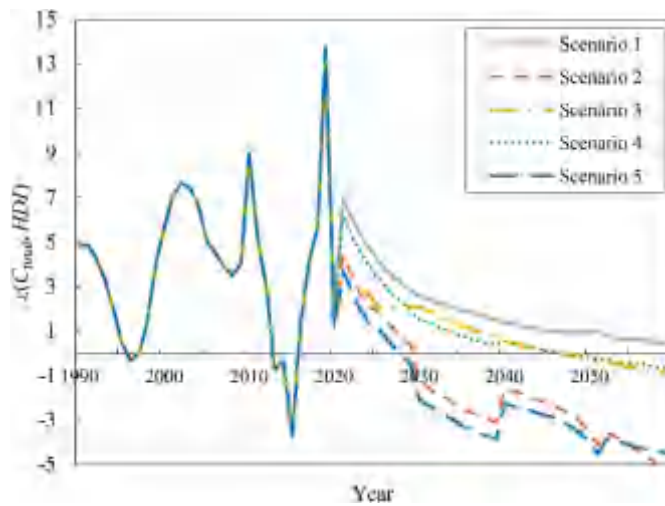


Fig. 11. The decoupling state between carbon emission and HDI.

consistently reduces and reaches the ideal state in the strong decoupling state. Compared with Scenarios 3 and 4 above, Scenarios 2 and 5 bring forward the arrival date of strong decoupling to 2030, saving >15 years of time and expenses.

Fig. 11 also presents a downward trend in five scenarios. Combined with Table 8, it is apparent that from 2021 to 2030, all scenarios will experience a 10-year expansive negative decoupling, especially in Scenario 1, which lasted the longest, up to 25 years. However, for Scenarios 2 to 5, expansive negative decoupling is also excusable in various policies implemented. From the perspective of policy, although the reduction of energy consumption and the adjustment of industry structure have restrained carbon emission to a certain extent, under the background where the global epidemic situation is still not optimistic, the import of energy is limited. As a result, China's economy is growing slowly. Measures such as limiting production capacity, restraining emissions, eliminating inefficient high-energy consuming enterprises, and accelerating the utilization of new energy cannot be achieved overnight. For instance, society needs to face the employment problem caused by industry transformation.

Additionally, the characteristics of “anti-peak-shaving” of new energy have also brought significant challenges to China's power system's consumption, frequency modulation, and stability. However, in 2031, when the expansive negative decoupling state ends, Scenarios 2 and 5 quickly turn into solid decoupling. Scenarios 3 and 4 also enter strong decoupling after the transition from 2036 to 2050. During this period, the goal of “carbon emission peaking in 2030” has been completed. China has changed from an extensive production model to a more refined production mode guided by environmental protection. As a result, people's living standards and social development have continuously improved, and carbon emissions have decreased steadily.

4. Conclusions

Systematic and comprehensive analysis of carbon emission impact factors and predictions can provide essential reference and theoretical guidance for China to formulate carbon emission reduction policies. This contribution proposed a holistic analytical approach of “factor decomposition, comprehensive evaluation, prediction, and decoupling analysis” to study China's carbon emissions from the integrated energy, economy, and environmental perspectives. The combination of extended Kaya Identity and LMDI method was introduced to establish the factor decomposition model of China's carbon emission using 11 factors from the perspectives of energy, economy, and society. Based on the factor quantification results, this manuscript uses the entropy weight method to construct a comprehensive evaluation model of China's power generation modes. Moreover, combined with nearly 40 years of carbon emission data, the system dynamics

Table 8
Decoupling elasticity of carbon emission and GDP, HDI.

Year	$\varepsilon(C_{\text{total}}, \text{GDP})$					$\varepsilon(C_{\text{total}}, \text{HDI})$				
	S1	S2	S3	S4	S5	S1	S2	S3	S4	S5
2021~2025	1.12	0.84	0.81	1.07	0.79	6.63	4.98	4.56	6.32	4.70
2026~2030	0.92	0.34	0.53	0.72	0.15	3.86	1.45	2.20	3.04	0.68
2031~2035	0.94	-0.50	0.71	0.54	-0.81	2.47	-1.24	1.87	1.43	-2.04
2036~2040	0.95	-1.36	0.56	0.35	-1.76	1.84	-2.60	1.10	0.69	-3.38
2041~2045	0.95	-1.46	0.35	0.27	-1.96	1.31	-2.02	0.49	0.38	-2.70
2046~2050	0.96	-2.28	0.05	0.06	-2.82	1.02	-2.40	0.06	0.07	-2.97
2051~2055	0.96	-3.99	-0.40	-0.28	-4.38	0.88	-3.61	-0.35	-0.24	-3.97
2056~2060	0.96	-7.19	-1.12	-0.82	-6.81	0.60	-4.44	-0.69	-0.50	-4.23

Legend

expansive negative decoupling	expansive coupling
weak decoupling	strong decoupling

model of China's carbon emission is built and verified to predict the trend of carbon emission over the next 40 years by introducing multi-scenarios of China's future energy transformation in energy structure. Finally, this manuscript introduces Tapio's decoupling theory to analyze the relationship between carbon emission and the development of the economy and society in multiple scenarios.

The decoupling and quantification of carbon emissions show that the increase in per capita income is the most critical factor driving the growth of carbon emissions in China, followed by the living scale effect, amount of thermal power generation, and proportion of thermal power generation. Energy intensity and prices can curb the growth of carbon emissions in China. Among them, the contribution of thermal power generation can reach 54.96 %. Although thermal power generation has energy and economic advantages, its negative environmental impact cannot be ignored. In contrast, clean energy's energy and economic indicators are lower than thermal power generation. However, the environmental benefits of clean energy development are beneficial to achieving China's "double carbon" goal. The prediction error of the system dynamics carbon emission model for China proposed in this paper is no >2.4 % on average. The multi-scenario prediction analysis found that improving energy efficiency and increasing the proportion of non-fossil energy consumption play a crucial role in reducing carbon emissions. The ideal outcome is that carbon emissions could peak at 12.276 billion tons in 2030. Moreover, the decoupling analysis suggests that the relationship between carbon emissions and economic growth and social development in China will eventually transition to a stable decoupling state in the next 40 years.

The above studies provide a systematic and coherent approach to establishing relevant carbon emissions policies at the national level. The approach can also be applied to provincial, municipal, and enterprise policy design. In addition, evidence-based policies and pathways can be developed based on their development history and characteristics.

5. Suggestions and outlook

Based on the carbon emission projections, the most optimistic option for China is to implement the policies proposed in Scenario 2 and reach carbon peaking around 2030, which would provide the shortest transition period. China can accelerate its energy transition by eliminating inefficient and energy-intensive industries and encouraging investment in green industries. Increasing the proportion of renewable energy in power generation is also reasonable. However, to better accommodate renewable energy, smart grids and integrated energy services may be ideal options to improve energy efficiency, reduce the cost of energy consumption, and promote the efficient use of demand-side resources.

This paper systematically analyzes China's carbon emissions from "factor decomposition, comprehensive evaluation, forecasting and decoupling analysis" based on a macro perspective. However, China is vast, from inland to coastal, from urban to rural areas, with unbalanced economic and social development among various regions and apparent differences in energy resource endowments. For example, the economic level of the south-east coastal region is generally higher than that of the northwest, which has more abundant energy resources than the southeast coastal region. Therefore, the study in this paper takes China's overall carbon emissions and multiple scenarios and ignores the impact of disparities between different regions. In order to formulate more accurate carbon emission reduction policies, the systematic research ideas proposed in this paper can be used to collect data from each province in China, and combined with the proposed factor decomposition, comprehensive evaluation, and prediction structure models, which can provide more diverse, targeted and feasible policy recommendations for the localized low carbon development of different provinces, and help China achieve the "double carbon" goal faster.

CRedit authorship contribution statement

Junhong Hao: Conceptualization, Writing – original draft, Funding acquisition, Project administration. Fei Gao: Software, Methodology, Writing –

original draft, Data curation, Validation. Xuanyi Fang: Data curation, Methodology, Writing – original draft, Validation, Writing – review & editing. Xinlu Nong: Investigation, Writing – review & editing, Writing – original draft, Visualization. Yingxin Zhang: Investigation, Methodology, Writing – review & editing, Writing – original draft. Feng Hong: Investigation, Methodology.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.scitotenv.2022.156788>.

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