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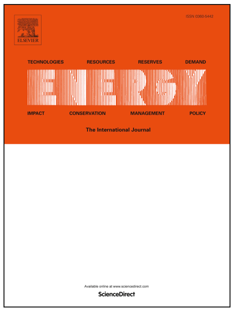

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Abstract:

For China to achieve carbon emissions peak and neutrality, the structural adjustment of both its economy and energy system is essential. In this study, a multi-objective optimization model based on the Input-Output approach is built to coordinate diverse policy targets vis-à-vis GDP growth, carbon emissions reduction, employment, and energy-saving of China from 2020 to 2030. The optimal structural adjustment pathways of China's economy, reflecting a high-resolution of available electricity generation technologies, under four policy preferences, are planned and the co-benefits and trade-off among multiple policy targets are detected. Our results reveal that while the energy-saving preference is more likely to hinder GDP growth (by -190 trillion yuan) and employment levels (by -60 million jobs), however, this preference is conducive to carbon emissions reduction (by -2.6 billion tons). Furthermore, our findings reveal that although the low-carbon preference does not undermine employment levels, however, it will restrain the GDP growth (by 109 trillion yuan). The integrated management of multiple policy targets would require the country's industrial structure to increase the proportion of low-carbon to total electricity generation to account for 71% by 2030 and the proportion of the services sector to the whole economy to account between 42%-51% by 2030.

Keywords: Carbon emissions; Employment; Trade-offs; Multi-objective optimization; Input-output analysis

1. Introduction

In September 2020, China announced its ambitious climate commitment to achieve peak carbon dioxide (CO_2) emissions before 2030 and carbon neutrality by 2060. To fulfill these commitments, Chinese policymakers are expected to focus on transforming the national economic system and societal values towards a future of low-carbon and sustainable growth. The sustainable governance of industrial and energy structures requires long-term systems thinking and an analytical understanding of the trade-offs between, often intertwined, policy objectives among socio-economic and environmental variables. Such trade-offs are of particular importance for developing countries, where socio-economic development and environmental sustainability influence future government policies. In the case of China, the world's primary energy consumer and carbon emitter (BP, 2020), targeted emission reduction targets, while maintaining economic development and high employment levels, are equal and critical policy priorities (NPC&CPPCC, 2021). These often competing directions lead to trade-offs in policy objectives., e.g., how emission targets may affect employment rates (in the short-term) or how the broader economy's welfare levels may be negatively influenced by the higher cost of carbon emissions abatement (Xue et al., 2015).

The adjustment of industrial and energy structures is considered one of the few systematic and effective policy strategies to achieve energy conservation and emission reduction (Li et al., 2020; Luan et al., 2021; Zhu et al., 2019). Incentives for investment in a large number of energy-intensive sectors and carbon-intensive sectors conflict with China's efforts to reduce carbon emissions (Bo et al., 2021; Wei et al., 2021; Zhou et al., 2021). Consequently, by appropriately adjusting China's industrial structure, i.e., transforming its major industries from energy-intensive to technology-intensive, economic development and reducing emissions can be concurrent. Meanwhile, shifting the electricity mix from thermal electricity, e.g., coal and oil, to low-carbon electricity, e.g., hydro, nuclear, wind, and solar power, has been widely regarded as a critical strategy to reduce carbon emissions (Reis et al., 2019; Tang et al., 2018). Although many studies have detected the influence of industrial or energy structure adjustment on carbon emissions reductions in recent years, there are few studies on how the adjustment strategy on industrial structure combined with the electricity mix will affect the competing economy, environment, and social sustainability policies and targets.

The Input-output Analysis (IOA) model is widely applied for examining relationships among the economy, energy, and the environment in industrial sectors by considering sustainable consumption concurrent with low-carbon production. With the addition of optimization models to an IOA model, policy scenarios can be simulated based on industrial structure and emission targets (Oliveira et al., 2016). To track various conflicting goals, multi-objective optimization is widely used to capture the nature of diverse sustainability goals (Liu and Hu, 2019), which are commonly conflicting and non-commensurate across the economic (e.g., GDP growth), environmental (e.g., carbon emissions reduction), and social e.g., employment (Wang et al., 2011) dimensions. By analyzing the synergy and trade-offs of multiple policy targets, policymakers can better clarify future policy priorities and formulate relevant industrial development strategies. Existing studies, however, have paid less attention to how industrial structure and electricity mix adjustments would impact the co-benefits and trade-offs among sustainability targets. Furthermore, it should be emphasized that the 14th and 15th Five-Year Plan (FYP) period (2020-2030) is critical for China's economy to realize sustainable development. In this avenue, exploring how changes in China's industrial structure and energy structure contributes to numerous sustainable development goals is of great value for the formulation of the 14th and 15th FYPs of country. In other words, by analyzing the synergy and trade-offs of multiple policy targets, policymakers can clarify the priorities of future policies and formulate industrial development strategies.

To contribute to the growing literature in the above-described policy research domain, we developed a multi-objective optimization model for China's structural adjustment of economic sectors to coordinate possible policy contradictions – caused by competing goals for GDP growth, carbon emissions reduction, energy conservation, and employment levels. The model proposed in this paper is distinct from previous models found in the literature and aims to contribute to the above-discussed research gaps. Specifically, the proposed model is based on high-resolution data of available electricity generation sectors, including both traditional electricity generation sectors (coal power and natural gas power) and low-carbon electricity sectors (hydropower, wind power, nuclear power, and solar power). From this data set and using IOA methods, we reveal policy preferences considering optimal GDP growth, carbon emissions, employment level, and energy consumption. Based on this analysis, the output structure of economic sectors is planned from 2020 to 2030. As coping with model uncertainty is critical for long-term policy planning and implementation (Lenzen et al., 2010; Su et al., 2010), in this paper, we examine uncertainties on estimated vital parameter values, e.g., carbon emissions intensity (carbon emissions per unit value-added), energy consumption intensity (energy consumption per unit value-added), and employment intensity (employees required per unit value-added).

The rest of this paper is organized as follows: In section 2, we overview the literature on optimization models for structural adjustment of economic sectors. Section 3 presents the formulation of the proposed multi-objective optimization model and subsequently, the data sources and parameters are described in Section 4. The results of our study are discussed in Section 5. A concluding discussion on policy implications and future research avenues is found in Section 6.

2. Literature review

Previous studies on the relationship among economy, environment, and society in China fall into two main streams. In the first stream, researchers have analyzed the interconnection of these three sustainability pillars from a single perspective by assessing the effects of one objective on others or from a specific sectoral perspective (Elshkaki, 2019; Guo et al., 2022; Song et al., 2018b; Zhou et al., 2019). The methods utilized in this type of research include econometric tools (Cheng et al., 2021; Wu et al., 2021), index assessment (Sheng et al., 2020; Zhang and Zhou, 2018), efficiency evaluation (Guo et al., 2017; Jiang et al., 2021), and decomposition methods (Huang and Matsumoto, 2021; Liu et al., 2021). For instance, Pan et al. (2019) analyzed China's provincial energy-related carbon emissions-economy nexus by adopting the decoupling coefficient and assessed the relationship between China's carbon emissions and economic variables by combining the static decoupling analysis and the dynamic vector autoregressive method. Wang et al. (2020b) explored the Water-Energy-Carbon Emissions nexus by assessing the embodied water and energy consumption and embodied carbon emissions. However, these studies either did not provide explicit solutions to meet divergent targets simultaneously or take the interconnection of economic sectors into account.

In the second stream, researchers have focused on optimizing solutions to achieve multiple conflicting objectives in perspective with the economy, energy, carbon emissions, and society (**Table 1** provides a summary review of these studies). The top-down computable general equilibrium (CGE) models have been applied frequently to climate and energy policies to assess China's emission reductions, energy use, and economic outcomes. For example, CGE models have been widely used to examine the economic impacts and emission reductions of carbon permit markets and taxes (Cao et al., 2021; Yuan et al., 2020). From a techno-economic perspective, the bottom-up energy system model enables users to compare the impacts of different technologies on energy systems and evaluate the best future alternatives for reducing greenhouse gas emissions (Chen et al., 2021; Zhang and Chen, 2022). However, the bottom-up approach fails to take into account the linkages between the energy system and macroeconomic sectors, thus neglecting the impact on those sectors. Combining the advantages of the top-down and bottom-up models, a hybrid model is applied to optimize the system's total cost or profit under the constraints of the economy, environment, and society (Yang et al., 2021).

Table 1 The main studies on optimization of policy targets in China's economy, energy, carbon emissions, and society.

Techniques used	Policy targets	Study period	References	Uncertainty treatments
IOA	GDP, pollutant emissions, energy consumption	2013-2020	Yu et al. (2018c)	-
	GDP, carbon emissions, employment	2013-2030	Yu et al. (2018b)	-
	GDP, carbon emissions, energy consumption	2017-2035	Yu et al. (2018a)	-
	GDP, energy consumption	2017	Xu et al. (2021b)	Slack variable
	Employment, energy consumption, water use, carbon emissions, pollutant emissions	2020	Wang et al. (2020a)	-
	Levelized cost of electricity, carbon emissions	2020-2050	Kang et al. (2020b)	-
	Levelized cost of electricity, carbon emissions	2020-2050	Kang et al. (2020a)	Robust optimization
	Cost of light-duty passenger transport system, carbon emissions	2020-2050	Kang et al. (2021)	Stochastic robust optimization
CGE	Energy consumption, carbon emissions	2017–2030	Cui et al. (2019)	Sensitivity analysis
	GDP, carbon emissions, energy consumption	2020-2050	Yuan et al. (2020)	Sensitivity analysis
	GDP, carbon emissions, air pollution	2020-2030	Xie et al. (2020)	Robustness analysis
Bottom-up energy system modelling	Energy transition cost, carbon emissions	2020-2050	Zhang and Chen (2022)	Monte Carlo analysis
	Energy consumption, carbon emissions	2030, 3040, 2050	Chen et al. (2021)	-
Bottom-up and top-down linked model	Energy consumption, carbon emissions, pollutant emissions, GDP	2020-2030	Yang et al. (2021)	-
Global climate models	Energy, carbon emissions, water	2021-2050	Suo et al. (2021)	Interval-parameter programming
Non-linear multi-agent intertemporal optimization model	Carbon emissions, energy consumption,	2018-2035	Xu et al. (2021a)	Monte Carlo analysis

The IOA method is widely applied for detecting the interdependence among economic sectors and socioeconomic and environmental effects (Leontief, 1970; Miller and Blair, 2009). Although the IOA highly depends on big data sets, which usually have a time lag, i.e., are only released every five years, and proportional hypothesis, it is considered as a ubiquitous and effective method for assessing the sectoral impacts of policy changes in the literature (Hartwig et al., 2017; Ogarenko and Hubacek, 2013; San Cristóbal, 2010). In the literature, many studies are using the input-output linear programming (IO-LP) techniques reported in China's energy and emission studies. For instance, Song et al. (2018a) explore potential pathways toward GHG emission peak before 2030 for China; Kang et al. (2020b) and Kang et al. (2020a) optimized the Chinese electricity generation mix to reduce the economy-wide carbon emissions from 2020 to 2050; Kang et al. (2021) assessed the optimal decarbonization pathways of light-duty passenger transport in China from 2020 to 2050.

To track various conflicting goals, an increasing number of studies developed multi-objective optimization models based on the IOA method to explore the optimal industrial production structure (Carvalho et al., 2015; de Carvalho et al., 2016; Oliveira and Antunes, 2004; Yu et al., 2018c). For instance, Oliveira et al. (2016) reviewed the different modeling approaches in the literature based on coupling IOA with multi-objective models. Yu et al. (2018b) constructed a multi-objective optimization model of economy-carbon emissions-employment based on the dynamic IOA model and explored the industrial structure adjustment plan to achieve China's energy-related carbon. Jiang et al. (2020) proposed a multi-objective optimization model to maximize economic development and minimize the embodied energy consumption from the consumption perspective. Wang et al. (2020a) proposed a multi-objective optimization model based on a multi-regional IOA to integrate the management of employment, energy consumption, water use, carbon emissions, and pollutant emissions by determining the policy-dominated industrial restructuring path. These studies have explored the relationships among economic, energy, carbon emissions, and employment goals and revealed that industrial restructuring has had profound and complex impacts on relevant policy goals.

Adjusting the energy structure is another way to promote carbon emission reduction from the perspective of structural adjustment (Yu et al., 2018a). Relevant studies have reaffirmed that the development of renewable energy generating capacity has a powerful impact on GDP growth, carbon emissions, and employment (Banacloche et al., 2020; Hondo and Moriizumi, 2017). Although the bottom-up energy systems modeling can provide a very extensive analysis for energy and climate policy based on precise technical details, the effects of changes in the energy system on the economic development of various industries are rarely taken into account. Without analyzing the impact of the electricity mix on these goals from the whole economic system perspective, the constraints of inter-sectoral input-output balance and sectoral production capacity will not be considered, resulting in deviation in policy evaluation. Some researchers have overcome this obstacle by decomposing and reaggregating the sectors in the IO table to separate the green activities from the traditional activities, or by adding a new group of sectors to the existing table (Jiang et al., 2019). For instance, Lindner et al. (2012) present a methodology to disaggregate the electricity sector of the Chinese national IO table into the transmission and distribution, and eight sub-sectors representing different types of generation technologies. Kang et al. (2020b) evaluated the capital-related carbon emissions of various generation technologies by endogenizing the fixed capital formation of electricity technologies.

On the whole, to the best of our knowledge, few researchers have explored how industrial structure adjustment, including different electricity sectors, can contribute to concurrent sustainability policy targets on GDP, emissions, energy, and employment in China. Furthermore, to enhance the policy flexibility, it is essential to consider some crucial uncertainties (Doukas and Nikas, 2020; Engau and Sigler, 2020). There have been some efforts to handle data uncertainty in optimization studies based on the IOA model (Tabatabaie and Murthy, 2021; Temursho, 2017). For instance, Henriques and Antunes (2012) accounted for model uncertainty associated with a model's coefficients by utilizing interval programming tools. More recently, the robust IO-LP model has been proposed for electricity capacity expansion planning (Kang et al., 2020b), and optimizing light-duty passenger transport (Kang et al., 2021). Although many achievements have been made in the field of IOA and optimization considering uncertainty, past research has paid less attention to the influence of the uncertainty of intensity changes on the multi-objective optimization of China's economic growth, emissions reduction, energy conservation, and employment levels.

3. Methodology

3.1. Model assumption

This model is based on the extended IOA model, aiming at the multi-objective problem of economy-environment-society to explore the optimal path of sectoral outputs adjustment. On this basis, the model further considers the impact of the uncertainty of energy consumption intensity, carbon emissions intensity, and employment intensity on the results. The model proposed in this study is based on the following assumptions:

(1) The technological conditions related to production technology remain unchanged for a certain period. However, since the economic system in China will be possibly different from 2020 to 2030, the inter-relationships among sectors may vary widely and lead to a bias in the estimates. The RAS method is a potential approach to updating the technical matrix to enhance the practicality of the IO table.

(2) Energy utilization technology is exogenous. The value of energy consumption intensity has been estimated by the trend extrapolation models for each sector and referred to Song et al. (2018a). The change in energy intensity will lead to the change in energy consumption of sectors at the same activity level. Then the optimal sectoral outputs in the optimal solution of the multi-objective optimization model will change. In order to measure the impact of changes in energy intensity on various policy objectives and outputs of each sector, this study conducts

an uncertainty analysis on energy intensity, detailed in Section 5.5.

(3) The basic assumptions for the input-output model are also valid, such as a specific homogeneous product in each sector and the returns to scale remain constant. These limitations are made for simplification. However, its advantages lie in the simplicity of the model and relatively limited number of hypothetical parameters, whereas more complex general equilibrium models usually rely on a far greater number of hypothetical parameters.

3.2. Objective functions

The basic equation for the distribution of sector *i*'s product, as given in:

$$x_i = \sum_{j=1}^{N} a_{ij} x_j + y_i \ , i = 1, \cdots, N \tag{1}$$

where x_i is the total output of sector *i*; a_{ij} denotes the direct input coefficient of sector *i* to produce one unit output of sector *j*, also known as an input-output technical coefficient; y_i is the final demand of sector *i*, which consists of household consumption, government consumption, fixed capital formation, and exports. *N* represents the number of sectors (*N*=48). This equation states that the total output in each economic sector equals the sum of intermediate demand and final demand.

We use the multi-objective programming models and methods coupled with the IOA model to support the process of economy-environment-social policy decision-making. The economic target is maximizing economic growth, which is the sum of the added value of all sectors; the environmental target is minimizing carbon emissions; the social target is maximizing national-level employment.

$$P: G(x) = \{\max f_1, \min f_2, \max f_3, \min f_4\} \tag{2}$$

$$f_1 = \sum_{t=1}^{T} \sum_{j=1}^{N} x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{3}$$

$$f_2 = \sum_{t=1}^{T} \sum_{j=1}^{N} ci_j^t x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{4}$$

$$f_3 = \sum_{t=1}^{T} \sum_{j=1}^{N} li_j^t x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{5}$$

$$f_4 = \sum_{t=1}^{T} \sum_{j=1}^{N} ei_j^t x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{6}$$

where f_1, f_2, f_3, and f_4 are scalar typed optimization objectives, representing the economic growth, carbon emissions, national-level employment, and energy consumption respectively.

For sector j in the t-th year, $x_j^t(1-\sum_{i=1}^{N} a_{ij}^t)$ is the sectoral value-added; ci_j^t is carbon emissions of per unit sectoral value-added; li_j^t represents workforce needed of per unit sectoral value-added; ei_j^t is energy consumptions of per unit sectoral value-added. T represents the number of planning years (T=11, from 2020 to 2030).

3.3. Constrains

(1) IO balance constrain. For each sector, the sum of intermediate demand and final demand should not exceed the total output.

$$x_i^t - \sum_{j=1}^{N} a_{ij}^t x_i^t \geq y_i^t,\ i=1,\cdots,N;\ t=1,\cdots,T \tag{7}$$

(2) Sectoral production capacity constraints. Given the stability of the economic system, sectoral production capacity should also be considered in the process of sectoral output adjustment besides the IO balance constrain. Therefore, the output of each sector should be limited within a certain range compared with the levels in the previous year:

$$\varphi_1 x_i^{t-1} \leq x_i^t \leq \varphi_2 x_i^{t-1},\ i=1,\cdots,N;\ t=1,\cdots,T \tag{8}$$

where $\varphi_2 > 1 > \varphi_1$. φ_2 and φ_2 are the upper and lower limits of the output growth rate for each sector, respectively.

(3) The constrain of the lowest annual economic growth. On the one hand, since China's economy has turned to high-quality development, we should not ignore the consequence of quality benefits and the ecological environment for the sake of economic growth. On the other hand, realizing industrialization and modernization needs moderate economic growth. As the largest developing country globally, development is still the foundation and key for China. Thus, setting the expected economic growth target can keep the economy running in a reasonable range, which is conducive to the realization of sustainable and healthy development.

$$\sum_{j=1}^{N} x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \geq (1+r_t) \sum_{j=1}^{N} x_j^{t-1} (1-\sum_{i=1}^{N} a_{ij}^t) \tag{9}$$

where r_t is the minimum growth rate of GDP in the t-th year.

(4) For the t-th year, the total energy consumption of all sectors cannot be more than the total energy supply. The upper limit of total energy consumption is formulated as follows (Yu et al., 2018b).

$$\sum_{j=1}^{N} E_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \leq \overline{ES}_t \tag{10}$$

where, for sector j in the t-th year, E_j^t represents energy consumption per unit value-added.

$\overline{ES}_t$ is the maximum energy supply in the t-th year.

(5) For the t-th year, the total number of employees should be limited within the labor supply in the whole society. The upper limit of the total number of employees is formulated as follows.

$$\sum_{j=1}^{N} l_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \le \overline{LS}_t \tag{11}$$

where $\overline{LS}_t$ is the maximum labor supply for the production process in the t-th year.

(6) Non-negativity constraint. All the decision variables in the model are non-negative variables.

$$x_i^t \ge 0,\ i=1,\cdots,N;\ t=1,\cdots,T \tag{12}$$

3.4. Model solving algorithm

In this study, the augmented ε-constraint method is used to model the proposed model. The essence of this method is a kind of a posteriori decision-making, that is, firstly, one objective is selected as the main objective for optimization; secondly, other objectives are taken as constraints, and the Pareto-optimal solution set is obtained by continuously adjusting constraint parameters; finally, the optimization results are sorted according to the preference of decision-makers. Compared with the prior decision represented by the weighted method, the ε-constraint method is more objective in the modeling, and the model results are closer to the demands of decision-makers.

In the ε-constraint method, the total added-value f_1 is taken as the optimization objective, the total carbon emissions f_2, the number of employees f_3, and the total energy consumption f_4 are taken as the constraints. The objective function in the multi-objective model in Section 3.2 is replaced by Eq. (13)-(16), then the multi-objective problem is transformed into a single objective optimization problem. The new parameters and variables of the model are described as follows:

E	Constant, the value range is usually [10^{-6}, 10^{-3}]. In this model, the value is 10^{-3}.
$ef_i, i=2,3,4$	Constraint parameters of the i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption), and the value range is between the maximum and minimum of the objective, which is obtained by the payoff table.
$sf_i, i=2,3,4$	Slack or residual variable for i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption).
Ng	The number of grid points. In this model, the value is 10.

$f_i^{\max}, i = 2,3,4$	Maximum value of the i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption).
$f_i^{\min}, i = 2,3,4$	Minimum value of the i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption).
$rg_i, i = 2,3,4$	The range of the i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption).
$g_i, i = 2,3,4$	Increment of the i-th objective (i=2: carbon emissions; i=3: employment; i=4: energy consumption).

$$\max\ f_1 + \varepsilon \times (-sf_2 + sf_3 - sf_4) \tag{13}$$

$$f_2 + sf_2 = ef_2 \tag{14}$$

$$f_3 \text{-} sf_3 = ef_3 \tag{15}$$

$$f_4 + sf_4 = ef_4 \tag{16}$$

To avoid too many weak Pareto-optimal solutions, we can replace sf_2, sf_3, and sf_4 in Eq. (13) with sf_2 / rg_2, and sf_4 / rg_4 to get the objective function of the augmented ε-constraint method, formulated by Eq. (17). rg_2, and rg_4 represent the range of the carbon emissions, employment, and energy consumption, respectively (as calculated from the payoff table), formulated by Eq. (18). ef_i represents the constraint parameters of the i-th objective, calculated by Eq. (19)-(21).

$$\max\ f_1 + \varepsilon \times (-sf_2 / rg_2 + sf_3 / rg_3 - sf_4 / rg_4) \tag{17}$$

$$rg_i = f_i^{\max} - f_i^{\min}, i = 2,3,4 \tag{18}$$

$$ef_2 = f_2^{\min} + \frac{rg_2}{(ng-1)} \times g_2 \tag{19}$$

$$ef_3 = f_3^{\max} - \frac{rg_3}{(ng-1)} \times g_3 \tag{20}$$

$$ef_4 = f_4^{\min} + \frac{rg_4}{(ng-1)} \times g_4 \tag{21}$$

The main procedures of the augmented ε-constraint are as follows: a) Calculate the payoff table of economic output, carbon emissions, employment, and energy consumption objectives by simply calculating the individual optima of the objective functions, as shown in Table 1. b) based on the payoff table, rg_i is calculated by Eq. (18), and the constant ε and the number of grids is set. c) The parameters ef_2, ef_3, and ef_4 are updated by iterating parameters g_2, g_3, and g_4 through Eqs. (19)-(21), and the optimization is carried out to maximize the total added value. If we find an effective solution, the efficient solutions are included in the Pareto solution set; therefore, the Pareto solution set including all the efficient solutions is obtained.

3.5. The final solutions screening method

Under the constraint conditions, each point of the Pareto optimal frontier is a compromise non-inferior solution satisfying the three objectives. To facilitate decision-making and further analyze the change of industrial structure when achieving economic growth, carbon emissions mitigation, and social employment growth, several representative solutions from the Pareto-optimal front need to be selected according to the decision-making preferences of the three objectives. Towards this end, we applied the Technique for Order Preference by Similarity to Ideal Solution method (TOPSIS) to select the solutions of the Pareto optimal frontier (Opricovic and Tzeng, 2004). It is a sequence selection technique of ideal goal similarity and a very effective method in multi-objective decision analysis (Boran et al., 2009). TOPSIS method is generally divided into three steps as follows:

(1) The formation of the decision matrix. The evaluation criterion of a multi-index decision-making problem is set as $C=(C_1,C_2,\cdots,C_n)$ the solution set is $M=(M_1,M_2,\cdots,M_m)$, the value of the criteria C_j for the solution M_i is $z_{ij}(i=1,2,\cdots,m,\ j=1,2,\cdots,n)$, and the multi-criteria decision matrix can be formulated as follows:

$$R=\begin{bmatrix} 0 & C_1 & C_2 & \cdots & C_n \\ M_1 & z_{11} & z_{12} & \cdots & z_{1n} \\ M_2 & z_{21} & z_{22} & \cdots & z_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ M_m & z_{m1} & z_{m2} & \cdots & z_{mn} \end{bmatrix} \tag{22}$$

(2) To eliminate the influence of different dimensions of each index on the calculation, the data should be normalized to construct a standardized decision matrix $R=(r_{ij})_{m\times n}$:

$$r_{ij}=\frac{z_{ij}}{\sqrt{\sum_{i=1}^{m} z_{ij}^2}} \tag{23}$$

(3) Constructing a weighted decision matrix. The dimensionless matrix is multiplied by the weight of each index to construct the weighted decision matrix $V=(v_{ij})_{mn}$:

$$v_{ij}=w_j\times r_{ij} \tag{24}$$

in which the W_j is the weighting matrix.

(4) Determine the ideal solution and negative ideal solution. It is defined that the solution obtained by taking the maximum value of each criterion is the optimal solution, the solution obtained by taking the minimum value represents the worst solution, and the positive and negative ideal solutions are represented by v^+ and v^- respectively, formulated as follows:

$$v^+ = \{\max v_{ij} \mid i = 1, 2, \cdots, m\} = \{v_1^+, v_2^+, \cdots, v_n^+\} \tag{25}$$

$$v^- = \{\min v_{ij} \mid i = 1, 2, \cdots, m\} = \{v_1^-, v_2^-, \cdots, v_n^-\} \tag{26}$$

where v_n^+ is the positive ideal solution of the *n*-th criterion, and v_n^- is the negative ideal solution of the *n*-th criterion.

(5) Distance calculation. The distance from the evaluation criteria of each solution to the positive and negative ideal solution is measured based on the Euclidean distance:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^+)} \tag{27}$$

$$d_i^- = \sqrt{\sum_{j=1}^{m} (v_{ij} - v_j^-)} \tag{28}$$

where d_i^+ is the distance between the *i*-th solution and the positive ideal solution, and d_i^- is the distance between the *i*-th solution and the negative ideal solution.

(6) Calculating the proximity between each solution and the ideal solution.

$$h_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{29}$$

where the greater h_i, the closer the solution M_i is to the ideal solution, and the better the solution is.

4. Data acquisition and processing

The Chinese non-competitive IO table in 2017 with 42 sectors, published by the National Bureau of Statistics (NBSC, 2017), was used to derive the input-output technical coefficient. As we suppose the technological conditions related to production technology remain unchanged for a certain period, the input-output technical coefficients during 2020-2030 remain the same as these in 2017. The Production and Supply of Electric Power sector in the IO table was disaggregated into electricity transmission and distribution sector and six electricity generation sectors, including coal power, hydropower, wind power, gas power, nuclear power, and solar power. Detailed information about the disaggregation of the electricity sector can be found in **Appendix A**. The final 48 economic sectors in the proposed model can be found in **Table A1**. The exogenous parameters of the planning period (2020-2030) are as follows:

(1) For the final demand data, firstly, we collect the competitive IO tables from 2002 to 2015 and the non-competitive IO table of 2017 from the National Bureau of Statistics and then

transform these competitive IO tables into the non-competitive IO tables by removing the imports from the intermediate use and final demand following the study by Weber et al. (2008). However, we find that total final demand varies so widely between 2002 and 2017 for different sectors that it is difficult to capture clear trends. Subsequently, we try to replace the changing trend of the final demand of each sector with the changing trend of the total final demand of all sectors, but this strong constraint condition is difficult to realize in the model. Therefore, we use the data of sectoral final demands in 2017, which means that we require that the model should always meet the sectoral final demands level in 2017 during the study period.

(2) The carbon emissions intensity and energy consumption intensity (listed in **Table A2-A3**). Most of the values of sectoral carbon emissions and energy consumption coefficients during 2020-2030 have been estimated according to the historical data and also referred to Song et al. (2018a). The carbon emissions coefficients of sub-divided electricity sectors are calculated by the proportion of carbon emissions from thermal power units. The energy consumption coefficients are obtained by the proportion of standard coal consumption for electricity generation.

(3) The employment intensity represents the sectoral workforce needed per unit of added value. We first calculate the historical employment intensity from 2010 to 2019 based on the historical value-added and employment by sector data found in the China Statistical Yearbook. We then estimate the employment intensity by sector from 2020 to 2030 using trend extrapolation models.

(4) The upper and lower limits of the output growth rate for each sector. According to the setting of Dong (2009), the output of each sector in the year is greater than 80% of that in the previous year and no more than 120% of that in the previous year.

(5) The minimum growth rate of GDP. To achieve steady economic growth, the minimum growth rates of GDP are set to 5% from 2020 to 2030 (Yu et al., 2018b).

(6) The maximum energy consumption and labor force. According to the policy of the Revolution Strategy for Energy Production and Consumption (2016-2030) (NDRCC, 2016) and sectoral energy consumption calculated based on the IO table in 2012 (NBSC, 2012), the maximum energy consumption in 2020 and 2030 is set to 5.2 and 6.3 billion tons of standard coal. The data for maximum energy supply in other years is calculated by the equal growth rate of limited energy consumption. The number of sectoral employees from 2020 to 2030 is forecast by trend extrapolation based on the latest historical data on the number of sectoral employees, which is derived from “Employment in the Sub-sectors” in the China Statistical Yearbook over the years 2010 to 2019.

5. Results and Discussion

5.1. Payoff matrix

The initial payoff table is reported in **Table 2**. The first row displays various objective values, while the last three rows list policy targets of multiple objectives. According to the solutions of a single-objective optimization model, the achievement of economic objectives is accompanied by the maximization of employment, indicating co-benefit effects between the economic and employment objectives. While achieving the maximum economic outputs brings more carbon emissions and energy consumption. Another notable result reveals a trade-off between the realization of the emissions reduction target and energy-saving targets.

Table 2 Payoff table

Objectives Units	Economy Trillion yuan	Carbon emissions Billion ton	Employment Billion people	Energy consumption Billion tce
Maximizing economy	1710.3	105.9	7.2	61.5
Minimizing carbon emissions	1435.8	101.5	7.2	58.3
Maximizing employment	1435.6	102.0	7.2	57.4
Minimizing energy consumption	1436.0	102.0	7.1	57.4

5.2. Pareto-optimal front and selected final solution

A set of Pareto solutions with 1239 solutions is obtained by solving the model, and each solution corresponds to a set of decision variables and multi-objective optimization results. **Fig. 1** illustrates the Pareto solution set, where the three-dimensional coordinate axis represents the total added value, total carbon emissions, and total employment respectively, the color gradient of these points indicates the amount of energy consumption, and the points represent the set of Pareto solutions.

Each Pareto-optimal front is a trade-off non-inferior solution to satisfy the three objectives under certain constraints. In contrast to one optimal solution of a single optimization problem, these solutions do not dominate each other. Facing numerous Pareto-optimal solutions, it is challenging for decision-makers to decide quickly. The TOPSIS method is applied to select several representative solutions from the Pareto-optimal front to facilitate decision-making. According to the four objectives of the model, we set up preference criteria set [f_1, f_2, f_3, f_4] and four preferences, namely the economy, low-carbon, employment, and energy-saving preferences. Then the preference information provided by the decision-maker is transformed into the weights of the criteria. Under the economy, low-carbon, employment, and energy-saving preferences, the weights set are [0.55 0.15 0.15 0.15], [0.15 0.55 0.15 0.15], [0.15 0.15

0.55 0.15], and [0.15 0.15 0.15 0.55] respectively. The results are shown in **Table 3**.

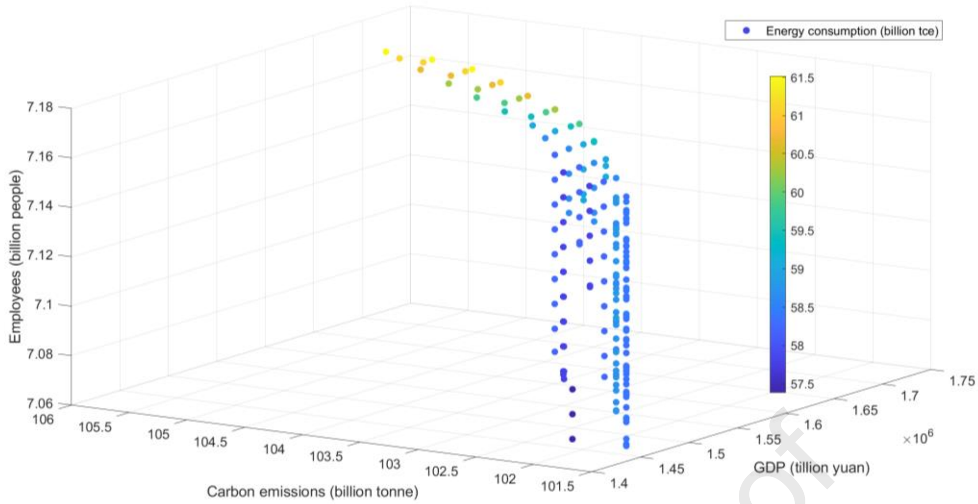


Fig. 1 Pareto front of EES multi-objective optimization model during 2020-2030

Table 3 The solution set under different decision preferences

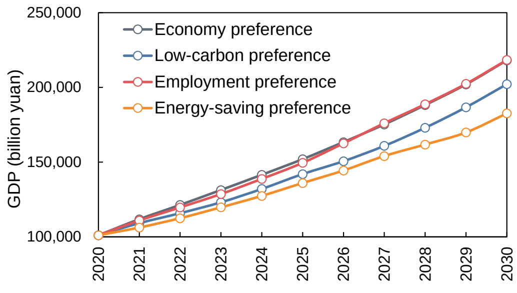
Objectives Units	Economy Trillion yuan	Carbon emissions Billion ton	Employment Billion people	Energy consumption Billion tce
Economy preference	1705.7	105.4	7.2	61.5
Low-carbon preference	1596.5	103.3	7.2	59.9
Employment preference	1696.6	105.4	7.2	61.1
Energy-saving preference	1515.6	102.8	7.1	58.2

5.3. The realization path of each objective

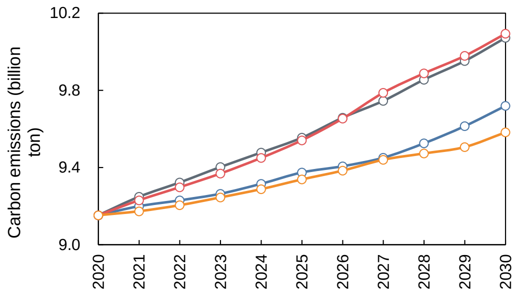
Based on the TOPSIS method, the annual optimal economic growth, carbon emissions, employment, and energy consumption under four preferences can be obtained, as depicted in **Fig. 2**. Regarding the economic objective, the total economic output realizes a steady growth during 2020-2030 under four preferences. Overall, the annual economic outputs under the economy preference and employment preferences are higher than those under other preferences. It is higher under the low-carbon preference than that under the energy-saving preference, indicating that policy preference dominated by energy conservation is more likely to hinder economic development.

As for the carbon emissions, the amount increases by 10% under the economy and employment preferences from 2020 to 2030. The carbon emissions will achieve the lowest growth rate under the energy-saving preference, which indicates that the energy-saving preference is beneficial to carbon emission reduction. Regarding to energy consumption, the policy preference dominated by full employment has the same promoting effect on energy consumption as economy preference. The energy consumption under the low-carbon preference is higher than that under the energy-saving preference, although lower than other preferences, which implies that with the strategy of low carbon driven development, energy consumption is still growing, but energy intensity is further reduced. It is worth mentioning that the optimal solutions under the four scenarios meet some targets released by the 14th national FYP (2020-2025), i.e., the energy consumption per unit of GDP will be reduced by 13.5%, and carbon emissions per unit of GDP will be reduced by 18% during the period (2020-2025). Our results indicate that energy intensity and carbon emissions intensity will respectively decrease by 23%-27% and 24%-30% for different preference scenarios in 2020-2025 –we also find a similar reduction in 2025-2030. This indicates that if the efficiency of energy consumption and the reduction of carbon emission in all sectors follow current trends and improve in the future, the national intensity targets will be more than fulfilled. However, we should also pay attention to some unexpected events that hinder the progress of energy efficiency improvements and emission reductions. For example, in reaction to epidemics, economic downturns, and unemployment pressures, some regional policymakers may impulsively embark on energy-intensive and or high emission projects. However, while unexpected events may pressure policymakers to make hasty decisions, achievements that have been made in energy efficiency improvements and carbon emission reductions should not be easily discarded.

In our study, carbon emissions will gradually rise to 9.6-10.1 billion tons in 2030, close to the peak point of carbon emissions proposed by several studies that cover a longer period (Li et al., 2017; Xu et al., 2020). For instance, the obtained results of carbon emissions under the low-carbon and economy preferences are also quite consistent with the time series of carbon emissions in the business-as-usual scenario and the deep mitigation scenario projected by Kang et al. (2020b). Moreover, for the energy consumption, the results are similar to findings in existing studies addressing net-zero emission issues in China. For example, one study (Mao et al., 2021) projects the aggregate energy consumption to increase by 21.96%, from 4.9 billion tce in 2015 to 6.0 billion tce in 2030. He et al. (2022) finds that China's primary energy consumption in 2030 is projected to reach 5.8 billion tce under the energy-target scenarios.



(a) GDP (billion yuan)



(b) Carbon emissions (billion ton)

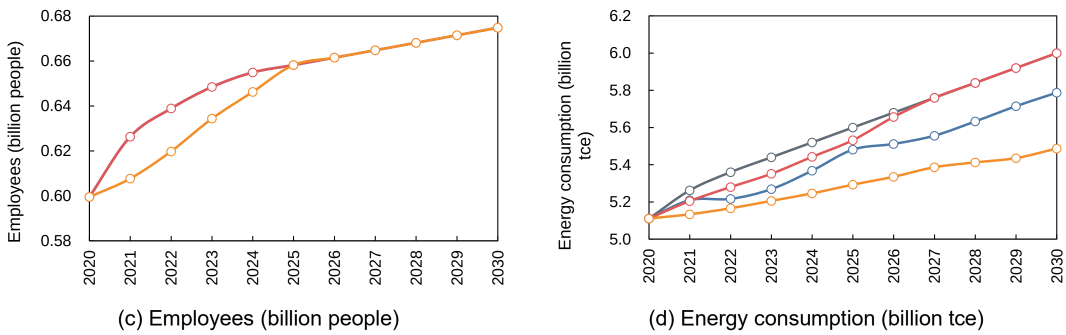


Fig. 2 The achievement path of Pareto-optimal solutions under four preferences during 2020-2030

In addition to the goals of economic growth, energy conservation, and carbon emission reduction, China's economic development goals also include full employment. "The 14th FYP for national economic and social development of China and the outline of long-term goals for 2035" (NDRCC, 2021) highlights the realization of fuller and higher quality employment and sets the goal of creating more than 50 million new jobs during the 14th FYP period. The results show that the number of employees will increase slowly under four preferences from 0.60 billion people in 2020 to 0.67 billion people in 2030. This is because the total labor supply mainly constrains the growth of the number of employed people in the future. Under the low-carbon, economic development, and employment policy preferences, the number of employed people in society can almost reach the maximum limit of the total labor supply. It is worth noting that before 2025, the number of employees under the energy-saving preference is significantly less than that under other preferences, but after 2025 it reaches the same as those under other preferences. The total employment under the energy-saving preference is -3%, -3%, -2%, and -1% lower than the average of the other three preferences in respectively, 2021, 2022, 2023, and 2024. The main reason for the difference in the growth of employees between the energy-saving preference and other preferences during the 2020-2025 period is found in the employment levels of the sectors. Specifically, in comparison to other scenarios, the employment levels of the *Construction*, *Comm. Eq.*, *Agriculture*, *Special Mach.*, *Elec. & Telecomms. Eq.*, and *Repair Services* sectors are significantly lower in the energy-saving scenario, i.e., respectively, -31%, -28%, -26%, -24%, -19%, and -14% lower than the average of the other three scenarios. Moreover, since the employment level is determined by the sectoral employment coefficient and the output level of each sector in this study, i.e., a lower level of sector activity leads to a lower level of overall employment, the difference in employment level under different scenario preferences is caused by the difference in the sectoral output level. To avoid trade-offs between energy-saving and full employment, our findings suggest that these sectors should reduce energy consumption intensity by improving energy efficiency in their future development.

5.4. Optimal sectoral total output

5.4.1. All economic sectors

In the proposed optimization model, the variables to be solved are the sectoral outputs. The optimal output structure of sectors under economy, low-carbon, employment, and energy-saving preferences during 2020-2030 are presented in **Fig. 3**. The final 48 economic sectors in the proposed model can be found in **Table A1** of **Appendix B**. To clearly demonstrate the sectoral output structure, 48 sectors are merged into six sectors according to the sector categories, including agriculture, mining, manufacturing, electricity-heat-water, construction, and services. In general, under four preferences, the manufacturing and services sectors account for the largest proportion of output value, followed by the construction and agriculture sectors. The output proportion of the manufacturing sector has a slight decline, while the output proportion of the electricity-heat-water sector will increase gradually from 2020 to 2030.

Specifically, under the economy preference, the proportion of the manufacturing sector continues to decline, from 41% in 2020 to 33% in 2030, while the output proportion of the services sector will gradually increase since 2025. The output proportion of the construction sector is on the rise from 2020 to 2025 and then in decline after 2025. There is an increase in the output proportion of agriculture and electricity-heat-water sectors. By 2030, the output proportion of agriculture, electricity-heat-water, and construction sectors will be the same. It is worth noting that the patterns under the employment preference are similar to those under the economy preference. A remarkable difference is that the proportion of the services sector is higher under the employment preference than under the economy preference, which is contrary in the construction sector. The results indicate that the contribution rate of the services sector to GDP shows an accelerating upward trend, and its ability to absorb the labor force continues to increase. At the same time, the promoting effect of the construction sector on economic growth and employment is rising first and then decreasing.

When under the low-carbon preference, the output proportion of the services sector has some slight fluctuations around 38%-40% before 2025 and then increases from 36% in 2025 to 44% in 2030. There is a gradual decline in the output proportion of the manufacturing sector during 2020-2030, while the output proportion of the construction sector rises from 11% in 2020 to 26% in 2027 and then drops to 22% in 2030. According to the data from "China Building Energy Consumption Research Report (2020)", the total carbon emission of the whole process of construction in 2018 was 4.93 billion tons, accounting for 51.3% of the national carbon emission, which indicates that the low carbon transformation of the construction sector has become the key to achieve the goal of carbon peak and carbon neutrality in China. Although carbon emissions in the construction sector show an overall growth trend, the growth of its energy consumption and carbon emissions has slowed down significantly (Zhang et al., 2019).

The patterns under the energy-saving preference are considerably variable from other preferences. First, the services sector's output accounts for the largest proportion with a gradually increasing trend, and the proportion of that is 51% in 2030. Second, the output share of the construction sector under this preference is smaller than other preferences, with an average proportion of 9%. Third, in line with the economic preference and low-carbon preference, the manufacturing sector's output will gradually shrink, while that of the electricity-heat-water sector will increase slightly. With the rapid release of energy-saving and emission reduction potential of primary and secondary industries and the increasingly apparent marginal diminishing effect of energy saving and emission reduction achievements, the service industry will become a new field of energy-saving and emission reduction in China. The results indicate that the energy-saving effect of developing the modern service industry is pronounced, while the energy efficiency of the construction sector needs to be continuously improved through the development of ultra-low energy consumption buildings and near-zero energy consumption buildings.

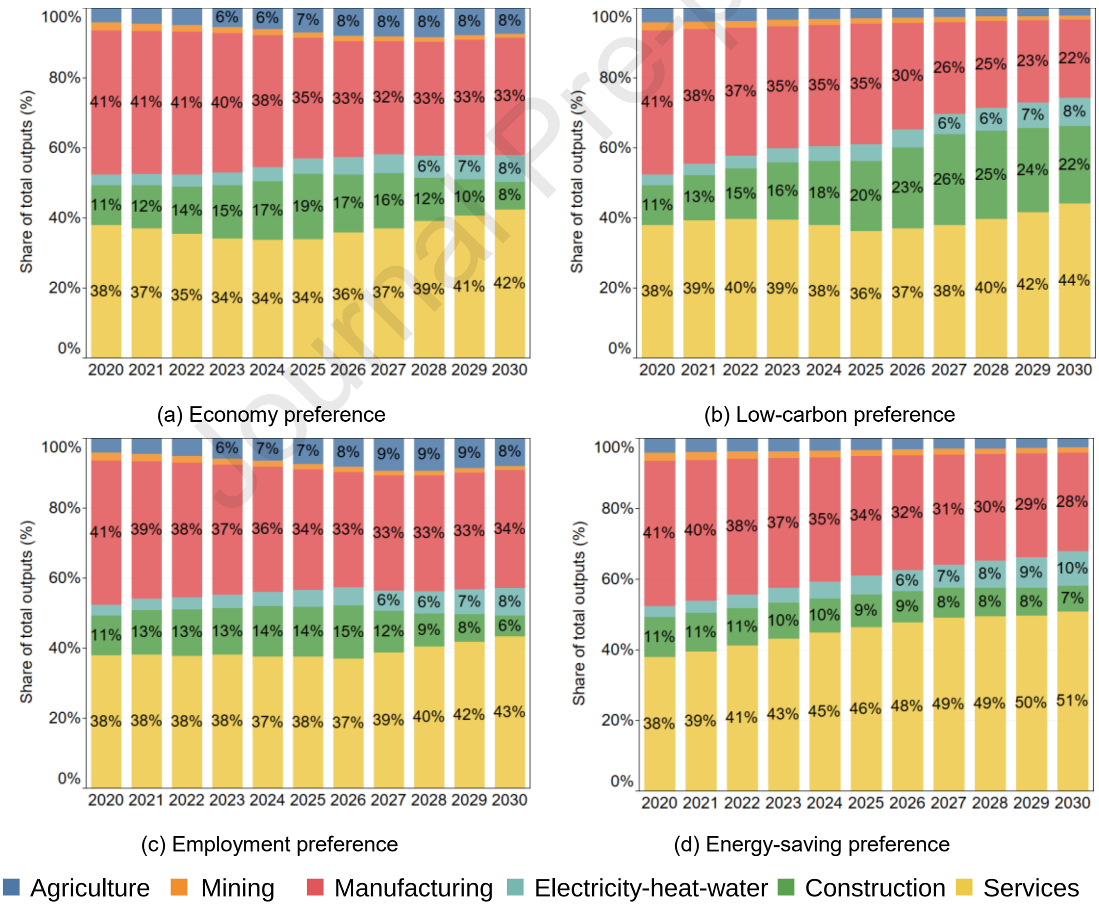


Fig. 3 The composition of six sectors' outputs under four preferences

Fig. 4 demonstrates the top ten sectors of economic output under various preferences. Regarding the economy preference, the primary sectors with high outputs are *Construction*, *Finance*, *Real estate*, *Comm. Eq.*, and *Agriculture* sectors. The patterns under the employment preference are quite similar to those under the economy preference. The main difference is that outputs of the *Construction*, and *Comm. Eq.* sectors are smaller under the employment preference than under the economy preference. The main reason may be that with the rapid development of big data, artificial intelligence, and other technologies, the capacities of the *Construction* sector to absorb the labor force will be weakened in the future.

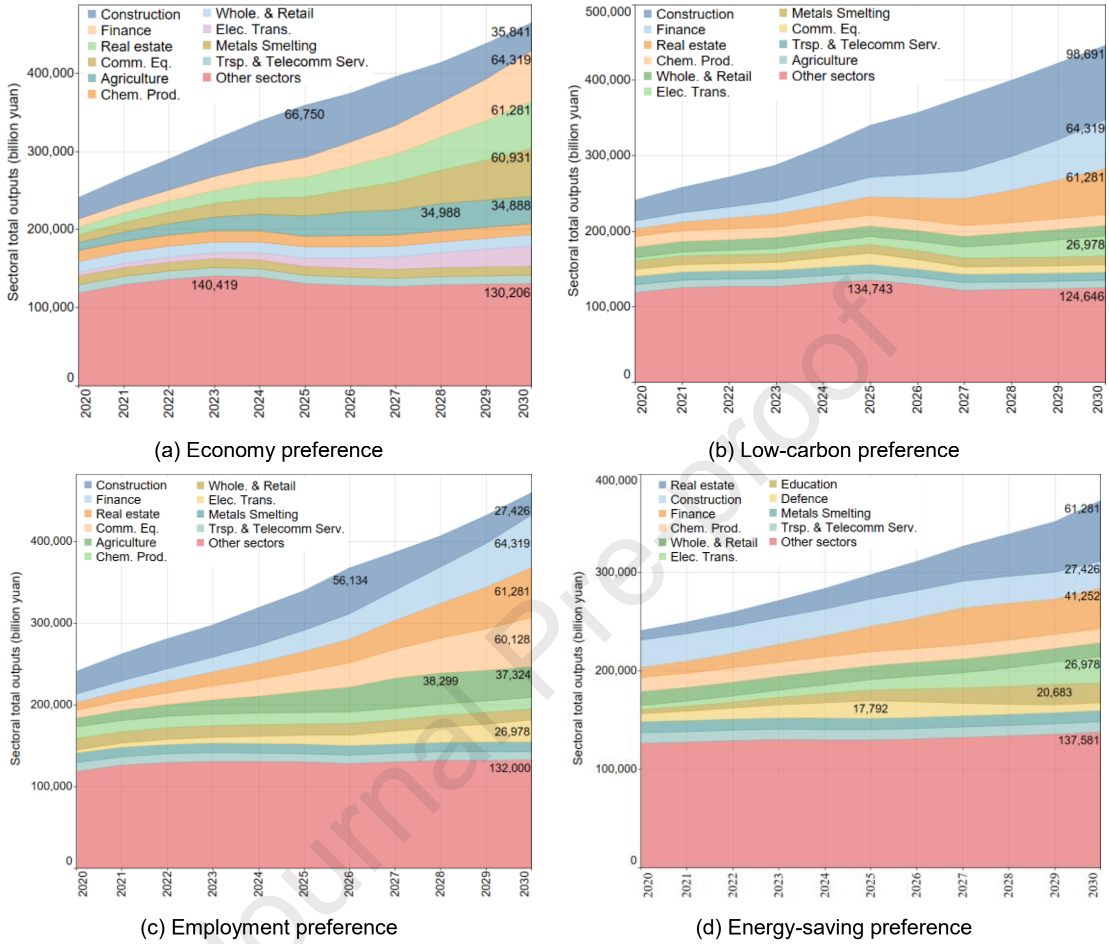


Fig. 4 The sectoral total outputs of main sectors under four preferences (the outputs of the major sectors in 2030 are labeled, as well as the larger output by sector before 2030)

Some differences can be observed under the low-carbon preference. Firstly, the *Construction* sector will also account for a larger proportion of the total sectoral output under this preference. Second, outputs in *Comm. Eq.*, *Agriculture*, and *Metals Smelting* sectors are much smaller under low-carbon preference than economy and employment preferences, which can be explained by the high carbon emissions intensity in these sectors. When under the energy-saving preference, the *Real estate* sector has the highest outputs, followed by the *Construction*, *Finance*, *Chem. Prod.*, *Whole. & Retail*, and *Elec. Trans.* sectors and all their outputs are on the rise. Another notable result is that only the *Real estate* sector has the same output as under other preferences when under the energy-saving preference. In contrast, the outputs of other primary sectors, for example, the *Construction*, *Finance*, and *Comm. Eq*. sectors, are lower than other preferences. The findings indicate that the energy intensity of the *Construction*, *Finance*, and *Comm. Eq*. sectors needs to be further reduced.

5.4.2. Electricity sectors

Fig. 5 demonstrates the development path of electricity sectors. The output patterns of each electricity sector have no difference in the four preferences because the outputs of coal-fired and gas-fired electricity sectors have almost no change. In contrast, the outputs growth of low carbon generation sectors will reach the maximum constrained by the model. The *Coal power* sector will be of significant importance for outputs of the electricity sector in 2020, accounting for 65% of the total outputs of all electricity sectors, and the share of the production in this sector is getting smaller, only 26% by 2030. On the other hand, the outputs of the *Hydropower*, *Wind power*, *Nuclear power*, *Solar power* sectors will increase sharply, showing an increase of more than 5 times. Among all low-carbon electricity sectors, the *Hydropower* sector has the most extensive economic output, followed by *Wind power*, *Solar power*, and *Nuclear power* sectors. According to the National Energy Administration of China, the installed capacity of renewable energy power generation reaches 934 million kilowatts by the end of 2020, including 370 million kilowatts of hydropower, 281 million kilowatts of wind power, 253 million kilowatts of photovoltaic power generation, and 29.52 million kilowatts of biomass power generation. Furthermore, the outputs of low-carbon electricity sectors will exceed that of traditional electricity sectors by 2025, and the output proportion of low-carbon electricity sectors will account for as much as 71% by 2030. With the proposal of China's carbon peak and carbon neutrality targets, the proportion of new energy in primary energy consumption is increasing, accelerating the replacement of fossil energy. The installed capacity of China's renewable energy power will maintain steady and rapid growth, showing a trend of dominating by wind power, solar power, and hydropower.

The patterns of electricity generation mix obtained by our study are much closer to that under the deep emission reduction scenario projected by other studies using a long-term model (Chen et al., 2021; Kang et al., 2020b; Zhang and Chen, 2022) – for example, the ratio of coal power is expected to decrease and its generation to remain stable from 2020 to 2030. While, unlike other models, the output of the hydropower sector in this study is higher than that of other renewable power sectors, such as wind power and solar power. The main reasons for these results are the following. Firstly, the present paper explores the carbon emission peak from the perspective of industrial structure optimization, while other long-term studies focus on minimizing the total cost of energy technology or other systems. Secondly, while other studies have considered only one objective, we consider four objectives simultaneously in this paper. Finally, this paper's electricity sector output differs from the generation capacity in other studies. This is important, as in addition to the generation capacity, the output takes into account the electricity price of different electricity generation types.

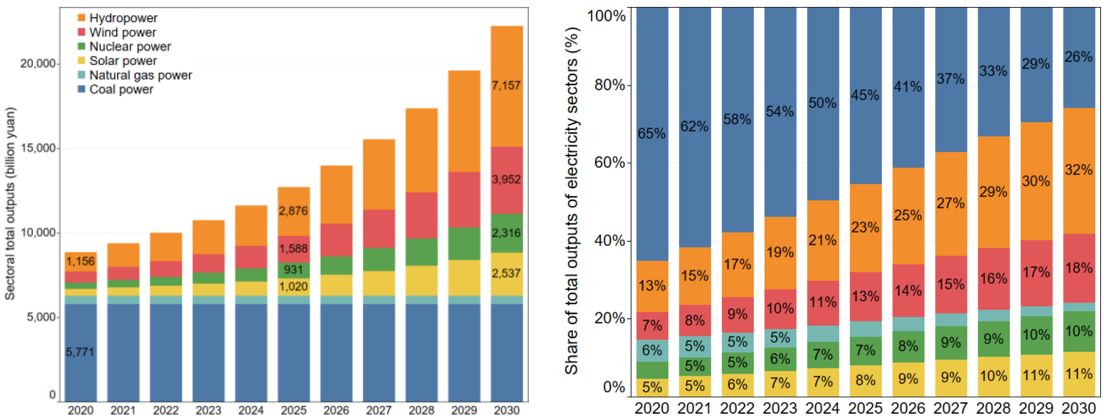


Fig. 5 The growth path of outputs and the composition of electricity sectors

5.5. Uncertainty analysis

In this optimization model, energy consumption intensity, carbon emissions intensity, and employment intensity are vital parameters. However, they have strong uncertainty as they are predicted according to historical data and by referring to the literature. Therefore, in this section, we explore the influence of these three factors on the optimal solutions of the proposed multi-objective optimization model. A discussion on the optimal solution set and the fluctuations of decision variables under four preferences when energy consumption intensity, carbon emissions intensity, and employment intensity fluctuate ±10%, ±20%, and ±30% of the predicted value, respectively, will be conducted. The value of fluctuation degree is defined as the ratio of the maximum fluctuation difference to the mean value.

5.5.1. Optimal solutions under uncertainty

The objective values of economic growth, carbon emissions, employment, and energy consumption under four preferences considering the uncertainty of energy consumption intensity, carbon emissions intensity, and employment intensity can be obtained, as depicted in **Fig. 6**. The results generally reveal that the changes in intensities only have a relatively large impact on the corresponding objectives, but little impact on other objectives; this is because the impact on output in different sectors presents two counteracting effects, i.e., promoting or inhibiting. For example, the uncertainty of carbon emissions intensity leads to greater fluctuation of emissions but has little impact on the achievement of other objectives. The uncertainty of employment intensity also leads to greater fluctuation of social employment and slightly affects the achievement of economic growth objectives. In contrast, the influence of energy consumption intensity on total energy consumption is smaller, and it also has a slight impact on the achievement of economic growth objectives. Our results suggest that the goal of energy-saving and emission reduction should be achieved by improving energy use efficiency and promoting the transformation of energy use structure to reduce energy consumption intensity and carbon emission intensity during the 14th and 15th FYP period.

Specifically, if the energy consumption intensity changes from 70% to 130%, the total energy consumption will fluctuate by 60% under four preferences. The range of total energy consumption is from 40.8 billion tce to 75.7 billion tce under the energy-saving preference, which is slightly less than that under other preferences. The fluctuation of energy consumption intensity will also lead to the fluctuation of 2% - 3% of economic output objectives under the economy and employment preferences. The objectives of carbon emissions and employment are insensitive to fluctuations in energy consumption intensity. Second, if the carbon emissions intensity changes from 70% to 130%, the total carbon emissions will fluctuate by 86% under four preferences. The range of total carbon emissions is from 72.3 billion tons to 134.2 billion tons under the low-carbon preference. Third, if the employment intensity changes from 70% to 130%, the total employment will fluctuate by 83% under the low carbon and employment preferences, slightly higher than that under the economy (78%) and energy-saving preferences (82%). As the energy consumption intensity and employment intensity increase, the constraints of total energy consumption and employment may no longer be satisfied, so the constraints are removed when the energy consumption intensity and employment intensity rise more than 10%, respectively.

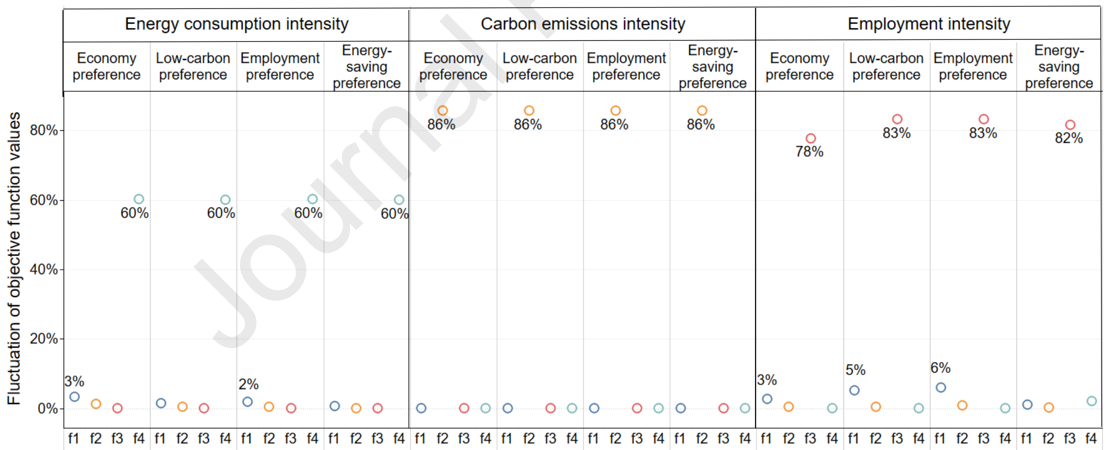


Fig. 6 Optimal solutions under four preferences considering the uncertainties of energy consumption intensity, carbon emissions intensity, and employment intensity (f1, f2, f3, and f4 represent the economic growth, carbon emissions, employment, and energy consumptions, respectively)

5.5.2. Optimal sectoral total output under uncertainty

In this part, we analyze how the outputs of all sectors change with the uncertainty of energy consumption intensity, carbon emissions intensity, and employment intensity, as depicted in **Fig. 7**.

First, the fluctuation of energy consumption intensity has a greater impact on the sectoral outputs under the economy preference. The most affected sectors are manufacturing sectors; for instance, the *Fiber Prod.*, *Special Mach.*, *Elec.& Telecomms. Eq.*, *Ord. Mach.*, *Trsp. Eq.*, *Oth. Mfg.* sectors. It is worthwhile to note that the *Instrum. & App.* sector is more vulnerable to the uncertainty of energy consumption intensity under the low-carbon preference, followed by *Comm. Eq.*, *Agriculture*, and *Special Mach.* sectors. Moreover, the outputs of several sectors are also affected to varying degrees under the employment preference, such as the *Education*, *Construction*, *Special Mach.*, and *Defence* sectors. The uncertainty of the energy consumption intensity has little impact on the sectoral outputs under the energy-saving preference, as our model assumes that the change in energy intensity of each sector is a whole change, not a relative change.

Second, the uncertainty of carbon emissions intensity only affects several sectors' outputs under the low-carbon preference, such as *Environ. & Pub.*, *Culture*, *Repair Services*, and *Oth. Mfg.* sectors, which indicates that the overall change of sectoral carbon emissions intensity will not significantly impact the structure of sectoral outputs. Third, the uncertainty of employment intensity affects the outputs of services and several manufacturing sectors. Specifically, the outputs of the *Whole. & Retail*, *Finance, Scientific Res.*, *Resident Serv.*, and *Culture* sectors are more vulnerable to the uncertainty of employment intensity under the four preferences. Under the economy preference, the *Whole. & Retail* sector has the greatest fluctuation degree, followed by *Culture*, *Agriculture*, *Resident Serv.*, and *Defence* sectors. When under the employment preference, the uncertainty of employment intensity has the greatest impact on the outputs of the *Accomm. & Cater.*, *Whole. & Retail*, and *Agriculture* sectors. The patterns of fluctuation of sectoral outputs under the low-carbon preference are similar to that under the employment preference, despite that the *Agriculture*, *Comm. Eq.*, *Special Mach.*, and several services sectors are not as sensitive as under the employment preference. It is worthwhile to note that under the energy-saving preference, the sectors whose outputs are affected by the uncertainty of employment intensity are almost the service sectors, except that the output of *Instrum. & App.* sector fluctuates 29.6%. Among the most affected service sectors, the *Whole. & Retail*, *Finance*, *Culture*, *Resident Serv.*, and *Accomm. & Cater.* sectors, of which the outputs fluctuate more than 70%.

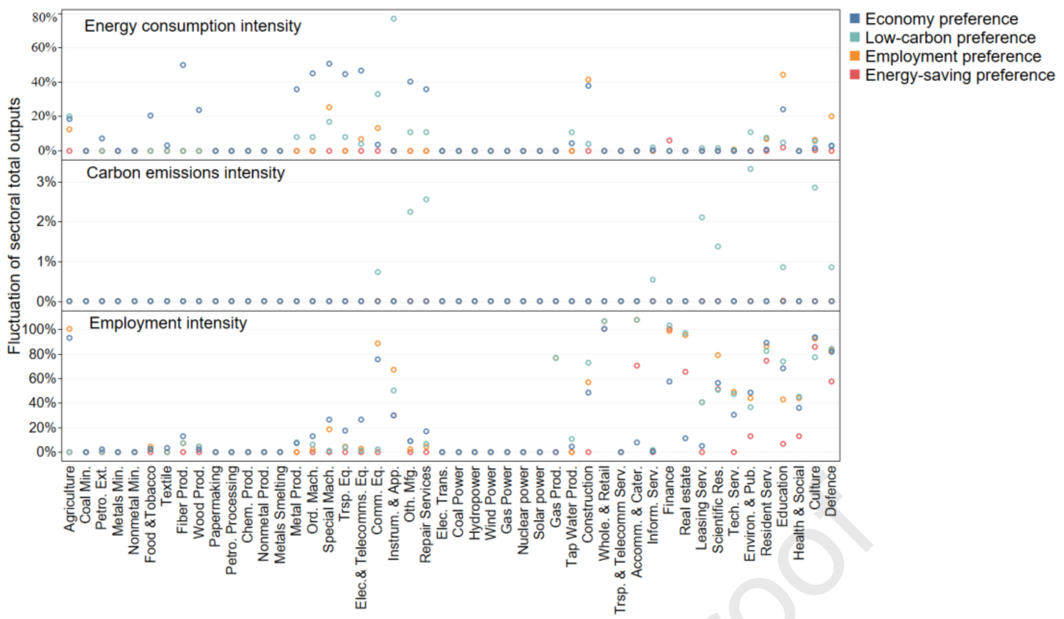


Fig. 7 The sectoral total outputs under four preferences considering the uncertainties of energy consumption intensity, carbon emissions intensity, and employment intensity

6. Conclusion

The Chinese government has set several development goals to achieve a balanced development of the economy, environment, and society. However, with the target year of 2030 fast approaching, China faces a crucial period to reach peak carbon emissions. Therefore, adjusting the industrial and energy structures to balance the conflicting national targets is in urgent need of solutions. This study adopts a multi-objective optimization model based on the IOA model to design an industrial structure adjustment pathway for the Chinese economy, considering the refined electricity mix and policy preferences. The main conclusions of our study are as follows:

First, the co-benefits and trade-off effects among economic growth, employment, carbon emissions, and energy consumption are revealed in this study. On the one hand, realizing GDP growth goals and increasing employment have a co-benefits effect, as expanding production capacity will provide more jobs. On the other hand, realizing carbon emission reduction targets will restrain the GDP growth and lead to the shrinkage of social employment to a certain extent. There is also a trade-off effect between energy conservation and carbon emission reduction; in other words, targets of emission reduction and energy saving may not be achieved simultaneously. Moreover, the results show that the number of employees under the energy-saving preference is significantly less than that under other preferences during the 14th FYP period, revealing that the energy-saving preference is more likely to hinder economic development, thereby influencing the employment level. On the other hand, carbon emissions will achieve the lowest growth rate under the energy-saving preference, indicating that this preference is more conducive to promoting carbon emission reduction. However, the energy-saving effect of low-carbon preference is not apparent, and the impact on GDP growth and employment is relatively small.

Second, this study provides the path of industrial structure adjustment to achieve the multiple policy objectives of GDP growth, emission reduction, employment level, and energy-saving under different policy preferences. The services sector will occupy an increasingly important position in the national economy when the policy goal is dominated by energy conservation and carbon emissions reduction. The policy preference of developing economy and ensuring employment is more conducive to the boom of manufacturing sectors. The output of the *Construction* sector accounts for a larger proportion under the low-carbon preference, while its development is restrained under the energy-saving preference, which indicates that the energy consumption intensity of the *Construction* industry needs to be further reduced. Vigorously developing low-carbon electricity generation technologies, such as hydropower, wind power, and solar power, will become an effective measure to achieve multiple goals of GDP growth, carbon emissions reduction, employment, and energy saving.

Third, under four policy preferences, economic outputs mainly come from services and manufacturing, such as the *Construction*, *Finance*, *Real Estate*, *Chem. Prod.*, *Whole. & Retail*, *Comm. Eq.*, *Elec. Trans.*, *Metals Smelting*, and *Trsp. & Telecomm Serv.* sectors. This indicates that these sectors will keep a strong development momentum in the next decade. Special attention should be paid to the *Instrum. & App.* sector when the policy preference is dominated by carbon emissions reduction, as it can not achieve the same high-growth development as under other preferences. Thus, continuous technology upgrading should be implemented in this sector to reduce its carbon emissions intensity. Moreover, the *Comm. Eq.* and *Agriculture* sectors, whose development is restrained under the low-carbon and energy-saving preferences, need further attention. Due to the older technology and equipment and unreasonable industrial structure resulting in considerable energy consumption and environmental pollution, it is necessary to improve the awareness of energy conservation and emission reduction and formulate relevant strategies in the *Comm. Eq.* sector. Regarding electricity sectors, the outputs of low-carbon electricity sectors will exceed that of traditional electricity sectors by 2025, and the output proportion of low-carbon electricity sectors will account for as much as 71% by 2030. Considering that the transformation of the electricity sector from high-carbon generation technologies to low-carbon generation technologies will lead to changes in infrastructure, production, consumption, and employment patterns, future policies on the development of low-carbon generation technologies should also focus on more economic and social impacts.

Fourth, this study explores how the uncertainty of energy consumption intensity, carbon emissions intensity, and employment intensity will affect the realization of GDP growth, carbon emissions reduction, employment, and energy-saving and the outputs of various economic sectors considering policy partiality. Results show that it will be more effective to reduce carbon emissions by reducing carbon emissions intensity rather than to by saving energy by curbing the energy consumption intensity. From the perspective of economic sectors, the industrial structure is more likely to change due to the uncertainty of energy consumption intensity. The uncertainty of energy consumption intensity will lead to a significant change in the outputs of some manufacturing and services sectors under different preferences. Moreover, the change in employment intensity slightly impacts on GDP growth, total carbon emissions, and total energy consumption and only makes the output of some sectors change to meet the constraints of the overall employee population.

Based on the above conclusions, we summarize the following policy implications on China's development in the recent 14th and 15th FYPs. First, to promote higher-quality development, not only emissions reduction and energy conservation but also securing stable employment levels should be considered. To compensate for temporary job losses due to energy conservation and emissions reduction, governments should stabilize and expand employment levels by encouraging companies to invest in R&D and innovation, increasing subsidies for R&D projects, and strengthening vocational skills training. Second, China's high-quality economic growth requires GDP growth to be decoupled from energy and electricity demand growth – here, the success of "decoupling" lies in placing energy- and carbon-intensive industries as the focus of structural adjustment. Therefore, it is necessary to increase the proportion of the tertiary industry in the GDP while curbing the secondary industry's scale of energy and electricity consumption, especially among the energy-intensive industries. Third, the coordinated realization of policy objectives of economic development, stable employment, energy conservation, and carbon reduction requires the electricity sector to accelerate the transition from coal-fired to zero-carbon power during the 14th and 15th FYPs.

There are some limitations to this study, and further efforts can be made in the future. First, due to the lack of recent official statistical information, China's IO table in 2017 was utilized, and the technical coefficient matrix is regarded as constant over time. The RAS method is a potential approach to updating the technical matrix to reduce estimation bias due to changes in China's economic system. Second, the current model only takes into account the uncertainties of carbon emissions intensity, energy consumption intensity, and employment intensity. However, some constant values set in the model, such as the upper/lower limits of sectoral output growth rate, are also uncertain in long-term planning. Those uncertainties can be further tackled in future works. Third, capital is not endogenized in the current methodology of the IOA model, which might neglect the capital-related carbon emissions from the renewable energy sectors and thus affect the results of our study. Kang et al.'s research (Kang et al., 2020b) may be a promising way to solve this problem in the future. Moreover, due to the limitations of the IOA model and the constraints and objective functions in the system optimization model, there will be a certain gap between the results of the optimization and the 14th FYP targets.

Supplementary material

Supplementary material associated with this article can be found.

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Highlights

- A multi-objective optimization model based on the Input-Output model is proposed
- The structural adjustment of economic sectors with fine-resolution power sectors is examined
- Coordinate contradictions caused by policy targets on economy-environment-employment
- Sectors that enable sustainability governance more balanced in reflecting three pillars are identified

Declaration of interests

☒ 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.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: