Quantifying the synergy and trade-offs among economy–energy–environment–social targets: a perspective of industrial restructuring

Shuo Zhang [a], Yadong Yu [a, *], Ali Kharrazi [b, c, d], Hongtao Ren [a], Tieju Ma [a, b, *]

[a] School of Business, East China University of Science and Technology, Meilong Road 130, Shanghai 200237, China

[b] International Institute for Applied Systems Analysis, Schlossplatz 1, Laxenburg A-2361, Austria

[c] CMCC Foundation—Euro-Mediterranean Center on Climate Change and Ca' Foscari University of Venice, 30175 Venice, Italy

[d] Faculty of International Liberal Arts, Global Studies Program, Akita International University, Yuwa City, Akita 010-1292, Japan

* Corresponding author: Yadong Yu (yuyd@ecust.edu.cn); Tieju Ma (tjma@ecust.edu.cn)

Abstract:

Protecting our environment while maintaining economic growth, requires a delicate balance among interlinked sustainable development policies. In this paper, we examine China's economic industries, including a high-resolution of the country's electricity sector during 2020-2030, using a multi-objective optimization model based on Input-Output analysis. This model investigates the synergy and trade-offs of sustainable development goals related to maximizing employment and GDP; minimizing energy and water consumption, CO_2 emissions, and five major pollutants to reveal a sustainable industrial structure adjustment pathway for China. Our results reveal that there exists both synergies and trade-offs among multiple objectives, e.g., synergy among goals of minimizing air pollutant emissions and trade-offs between minimizing energy consumption and maximizing employment. Through the planned industrial restructuring period (2020-2030), the GDP, employment, carbon emission, and energy consumption will increase respectively by, 96.1%, 7.2%, 16.8%, 16.8%, and 6.3%, while pollutant emissions would decrease. Moreover, the direction and strategy of industrial structure adjustment with energy and water conservation as the leading policy priorities are highly recommended policies. Our model demonstrates how the synergies and trade-offs among multiple policy targets can empower policy-makers, especially in developing nations, to make more informed and optimized industrial structure adjustment policies.

Keywords: Synergy; Trade-offs; Carbon emission; Pollutant emissions; Multi-objective optimization; Input-output analysis

1. Introduction

To achieve the ambitious goals of reaching peaking carbon emissions by 2030 and carbon neutrality by 2060, the Chinese government is deploying coordinated governance of pollution and carbon emission reduction across the country's provinces, especially those with high coal consumption (NDRCC, 2021). Since greenhouse gases and air pollutants come from the same source, measures to reduce fossil fuel consumption will reduce both the emission of air pollutants and carbon, leading to the co-benefit of improved air quality (Shindell and Smith, 2019; Wang et al., 2022). The coordinated policies to tackle carbon and air pollution will also affect economic growth and employment (Wei et al., 2020). On the one hand, reducing emissions of pollutants has direct economic and social benefits through reduced disease rates and increased labor productivity (Johnson et al., 2020; Li et al., 2020a). On the other hand, China's industrial structure, dominated by energy-intensive industries and energy structure, e.g., coal consumption, has not been fundamentally transformed towards more sustainable scenarios. Therefore, emission reduction measures, such as limiting coal consumption, will make energy-intensive industries face fundamental economic sustainability problems, including, for example, a decline in production capacity, economic stagnation, and unemployment (Yang et al., 2021b).

The primary challenge for policymakers is to strengthen environmental pollution control and carbon emission reduction while maintaining steady economic growth, avoiding stagnation, and a decrease in livelihoods through unemployment. The lack of experience in this public policy domain, especially among developing countries, necessitates a comprehensive consideration of social, economic, and environmental challenges, and the interaction of ensuing policy objectives (Dissanayake et al., 2020; Jin et al., 2018). Towards this end, researchers have made much effort in exploring the synergy and trade-offs among multiple policy targets. Synergy effects refer to measures for one policy goal, which is also conducive to realizing other goals. For example, research shows a synergy effect between carbon and $PM_{2.5}$ emissions reduction. As both emissions are often from the same source, actions taken to reduce carbon emissions also reduce $PM_{2.5}$ air pollutants (Driscoll et al., 2015). In contrast, the trade-off effect refers to challenges emerging as an aftereffect of implemented solutions for a separate environmental objective. For example, large-scale water dams provide hydropower and irrigation reservoirs; however, such infrastructure may negatively affect ecological systems and their biodiversity (FAO, 2014).

Numerous researchers have examined the experience of China in benefitting from the synergies of multiple environmental and economic policy targets (Guo et al., 2022). For example, Feng et al. (2018) analyzed the synergies of CO_2 and NOx control in China's cement industry. Alimujiang and Jiang (2020) examined the synergies of promoting electric vehicles in Shanghai and CO_2 reduction. Wei et al. (2020) explored the synergy between China's future electricity generation mix and carbon mitigation. However, these studies are from a single-sectoral perspective and do not consider inter-sectoral effects. This is while more researchers have come to conclude the need for a system-wide and holistic understanding of all sectors in devising sustainable transformation pathways (Cheng et al., 2021a; Zhang et al., 2021b). In this light, researchers have proposed multi-objective optimization models at a multi-sectoral level to reveal optimal solutions for policy targets, e.g., carbon emission reduction and economic growth (Yu et al., 2018b; Yu et al., 2018c). However, these efforts only consider a limited set of policy targets, e.g., three or four targets, and do not examine the synergies and trade-offs among multiple policy targets. In China, the Five-Year Plan (FYP) sets out systematic plans for major national construction projects, the distribution of productive forces, and the critical proportion of the national economy. It sets goals and directions for the vision of national economic development. The 14th and 15th FYP period (2020-2030) is a vital stage for China's industrial development to transform from scaling economic growth to high-quality sustainable growth. Furthermore, this period is a strategic opportunity for achieving peak carbon emissions and carbon neutrality. In this avenue, to contribute to China's 14th and 15th FYPs, we explore the synergy and trade-offs, from the perspective of industrial restructuring, among the economy, society, carbon emissions, energy, and environmental targets.

In this paper, we propose a multi-objective Input-Output (IO) optimization model and demonstrate its value by examining the high-resolution of China's electricity sector, which includes both traditional electricity generation sectors (coal and natural gas power) and low-carbon electricity sectors (hydropower, wind, nuclear, and solar power).

This model reveals essential insight into the synergy and trade-offs among concurrent policy targets, including maximizing GDP and employment levels and minimizing carbon emission, energy consumption, water consumption, and minimizing five major environmental pollutants, i.e., sulfur dioxide (SO_2), nitrogen oxides (NOx), soot and dust (SD), chemical oxygen demand (COD), and ammonia nitrogen (AN). We choose these pollutant indicators for policy relevance, i.e., indicators that have received particular attention from the national government in the 14th FYP, and data availability. Furthermore, this study sheds light on the following issues: 1) What are the synergies and trade-offs among China's socio-economic and emission reduction goals during the 14th and 15th FYP period? 2) While attaining peak carbon emissions, how will the synergy or trade-offs among relevant policy objectives change? 3) In which critical sectors are the most significant trade-offs and synergies among multiple objectives? 4) How can the path of industrial structure adjustment in the electricity sector change to achieve multiple sustainable development policy objectives?

The remainder of this paper is organized as follows. Section 2 briefly reviews the literature on current environmental synergy studies. Section 3 focuses on the methodologies and data used in this study. Section 4 shows the results of the multi-objective optimization model. The final section summarizes the key findings and discussion.

2. Literature Review

Many efforts have been made to detect the synergy among economy, environment, and employment, including policy analysis, model application, and case discussion. When focusing on the synergy of carbon emission reduction and environmental emission reduction, there is an increasing number of studies that reveal that China's environmental policies to alleviate air pollution can bring co-benefits to carbon emissions mitigation (Lu et al., 2019; Nam et al., 2013; Xu et al., 2021), health (Harlan and Ruddell, 2011; Johnson et al., 2020; Liang et al., 2019), and the economy (Cao et al., 2012; Dong et al., 2015b). On the other hand, climate actions to reduce fossil fuel consumption also have substantial benefits, including air quality (Li et al., 2019), public health (Scovronick et al., 2019), the mitigation cost impact (Rauner et al., 2020), and even energy security (Mondal et al., 2010). Moreover, as one of the three pillars of sustainable development, social employment levels have always focused on policy attention. Therefore, guaranteeing the employment level's stability simultaneously is a topic of concern, especially in the context of carbon emission reduction and environmental pollution control (Dell'Anna, 2021; Schreiner and Madlener, 2021). A volume of research has evaluated the employment impact of the decarbonization pathway (Arvanitopoulos and Agnolucci, 2020; Kuriyama and Abe, 2021), energy transition (Füllemann et al., 2020; Yang et al., 2021a), and pollution emission reduction process (Li et al., 2020b; Zhong et al., 2021).

Various methods have been applied in this field. The methods utilized in the relationship analysis among economy, environment, and society include econometric tools (Cheng et al., 2021b; Wu et al., 2021a), index assessment (Sheng et al., 2020; Zhang and Zhou, 2018), efficiency evaluation (Guo et al., 2017; Jiang et al., 2021), and the decomposition method (Huang and Matsumoto, 2021; Li et al., 2021; Liu et al., 2021), etc. Recently, most environmental synergy studies link "top-down" approaches like Computable General Equilibrium (CGE) models to local pollutant models, which focus on individual pollutants that can be measured directly and rely heavily on traditional numerical modeling (Huang et al., 2021; Zhang et al., 2020). In this avenue, Dong et al. (2015a) applied CGE combined with an air pollution model to project future carbon and air pollutants emissions in China between 2005 and 2030. Some studies link the energy technology-rich "bottom-up" approach to the pollution model, mainly focusing on one specific industrial sector. For instance, Cao et al. (2019) focused on China's power sector and examined carbon mitigation and human health co-benefits from the co-abatement of conventional air pollutants. Du et al. (2021) assessed the synergistic effects between air pollutants, i.e., SO_2, NOx, PM, and carbon emission, through emission reduction measures (structurally and technically) in the coal-fired power industry. Moreover, an integrated assessment framework by combining a bottom-up multi-resolution emission inventory, a top-down CGE model, or a health assessment model have been applied to explore the air quality and health co-benefits of carbon emissions reduction (Dong et al., 2015a; Tong et al., 2020; Wu et al., 2021b).

The IO analysis has been applied to detecting the interdependence among economic sectors and socio-economic and environmental effects from the perspective of the entire supply chain (Chen et al., 2018; Wu et al., 2020). For instance, Song et al. (2018) explored potential pathways toward GHG emission peak before 2030 for China. Some studies optimized the Chinese electricity generation mix to reduce the economy-wide carbon emissions from 2020 to 2050 (Kang et al., 2020a; 2020b). Facing the challenge of addressing multiple conflicting policy targets on the economy, carbon emissions, environment, and society, the IO analysis has recently been combined with a multi-objective optimization model to capture the diverse aspects and to generate optimal solutions to achieve multiple conflicting objectives. For example, Yu et al. (2018a) proposed a new economy-carbon emission-costs multi-objective optimization model to explore how China's energy-related carbon emission peak could be achieved by adjusting the country's structure of energy consumption between 2015 and 2035. Furthermore, For example, Wang et al. (2020) proposed a multi-objective optimization model based on multi-regional IO analysis, which integrates employment management, energy consumption, water use, carbon emission, and pollutant emissions. However, this study only examines one year, i.e., 2020, which is insufficient to reflect the trade-off and synergy among multiple policy objective trends over time. Several studies have also examined the interaction among economic, environmental, and social targets towards the long-term goal of peak carbon emissions. For instance, Yu et al. (2018c) investigated the impact of industrial structure adjustment on China's energy-saving and pollution reduction goals from 2013 to 2020 by developing an energy-environment-economy model based on the IO model. However, these long-term studies only consider limited policy targets (three or four targets, such as economic growth, carbon emissions reduction, and employment) and do not examine the synergies and trade-offs among multiple policy objectives. This provides limited insights for China to meet its sustainable development objectives for the economy, carbon emissions, energy, society, and environmental pollutants.

Based on the discussion above, this study contributes to the literature in the following aspects. First, we propose a multi-objective IO optimization model that considers China's multiple sustainable development elements, including maximizing GDP and employment and minimizing carbon emission, energy consumption, water consumption, SO_2, NOx, SD, COD, and AN emissions. When considering different policy orientations, the synergy and trade-offs among multiple objectives can be identified. Second, the optimal pathway of China's industrial and electricity structure is examined from the proposed model during the 14th and 15th FYP period (2020-2030).

3. Methods and Data

3.1. Multi-objective optimization model

Designing for a long-term pathway involving multiple goals and criteria design often requires considering the synergy and trade-off among multiple development elements regarding economic development, employment, and environmental sustainability. The multi-objective optimization approach is an operational research technique suitable for addressing decision-making problems with multiple conflicting goals, enabling a deeper understanding of the trade-offs between all the objectives considered (Oliveira et al., 2016). Thus, we propose a multi-objective optimization model based on the IO model to explore the comprehensive management measures of the economy, society, resources, and environment. The four dimensions are represented by GDP, employment, energy and water consumption, and emissions (carbon emission and other environmental pollutant emissions). The whole model can be divided into four aspects: the model assumptions, objective functions, constraint conditions, and model solving.

3.1.1. Model assumptions

The model for the problem to be solved in the present paper was based on three assumptions. First, the technology conditions related to the sectoral production technology remained unchanged from the level in 2018 for the model periods, from 2020 to 2030. Since the economic system in China will be possibly different from 2020 to 2030, the inter-relationships among sectors can also be various, leading to a bias in the estimates. Second, the basic assumptions of the IO model are also reasonable, such as each sector only produces a specific product, and the returns to scale remain constant. However, its advantages lie in its simple model and relatively limited assumed parameters. In contrast, the more complex general equilibrium model usually relies on a large number of assumed parameters, so the IO model is considered to be an effective solution for the assessment of sectoral impacts of policy changes in the literature. Third, this study focuses on the industrial sectors, so the household sector's energy consumption, water consumption, and environmental pollutant emissions are not considered in this study. The secondary industry is the main force of energy consumption in China, while the energy consumption of the residential sector accounts for less than 15% of the total. Therefore, excluding the residential sector from the model slightly impacts the results.

3.1.2. Objective functions

a) The maximization of cumulative added value

The long-term goal of 2035 puts forward that the per capita GDP should reach the level of moderately developed countries. As the first two FYPs are at the intersection of the “two centenary” goals, the 14th and 15th FYPs should lay the foundation for a longer-term development strategy. Thus, economic development remains the top priority, and the maximum cumulative value of GDP in the planning period (from 2020 to 2030) was considered the first objective, namely,

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

where for sector j in the t-th year, a_{ij}^t was the 48×48 technical coefficient matrix which was derived from the IO table, reflecting the intermediate material flow among 48 sectors; x was the 48×11 decision variable, indicating the total outputs of 48 sectors in the planning period (2020-2030). $x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t)$ was the added value. T denoted the number of planning years ($T = 11$), and N represented the number of sectors ($N = 48$).

b) Minimization of cumulative carbon emission

Industrial production activities generate the majority of China's total carbon emissions. For the goals of emissions to peak in 2030 and carbon neutrality in 2050, the carbon emission of sectors must be controlled. Thus, the minimization of cumulative carbon emission in the planning period (from 2020 to 2030) was set as the second objective, expressed as,

$$\min \quad f_2 = \sum_{t=1}^{T}\sum_{j=1}^{N} ci_j^t x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{2}$$

where ci_j^t were 11×48 parameters, denoting the carbon emission of per unit sectoral added value in year t.

c) Maximization of the cumulative number of the labor force

In the post-COVID-19 era, how to guarantee employment stability and security has become a significant issue that all countries must face, especially China, the largest developing country. In order to successfully achieve the carbon emission reduction target, it is inevitable to adjust the industrial structure, focusing on industries with high-emission and high-energy consumption. Appropriate industrial structure adjustment will promote the labor force flow among industries to ensure the stability of employment. Thus, the maximization of the cumulative labor force from 2020 to 2030 was set as the third objective, namely,

$$\max \quad f_3 = \sum_{t=1}^{T}\sum_{j=1}^{N} li_j^t x_j^t (1 - \sum_{i=1}^{N} a_{ij}^t) \tag{3}$$

where li_j^t were 11×48 parameters, representing the workforce needed per unit sectoral added value in year t.

d) Minimization of cumulative energy and water consumption

The high proportion of fossil energy consumption is the primary driver of carbon emission. Therefore, minimizing the cumulative energy consumption in the planning period was the fourth objective, as depicted by Eq. (4). Moreover, the shortage of freshwater, an imbalance between water resources and demand in temporal and spatial dimensions, has become a threat to the sustainable development of some rapidly developing countries such as China. For example, in 2020, 464.28 billion m^3 of water resources in China have been used for production activities, accounting for 79.8% of the total water consumption (MWRPRC, 2021). Thus, effective management of water resources in industrial sectors must be conducted to cope with the increased demand for water resources due to the increase in population and the improvement of people's living standards. Therefore, the fifth objective was minimization of the cumulative water resources consumption in the planning period, as depicted by Eq. (5).

$$\min\ f_4 = \sum_{t=1}^{T}\sum_{j=1}^{N} ei_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{4}$$

$$\min\ f_5 = \sum_{t=1}^{T}\sum_{j=1}^{N} wi_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{5}$$

where ei_j^t and wi_j^t were 11×48 parameters, representing the energy and water resources needed per unit sectoral added value in *t*-th year, respectively.

e) Minimization of various environmental pollutant emissions

Strengthening ecological and environmental protection and resolutely fighting the battle for pollution prevention and control have become significant decisions and arrangements in China. By 2020, the overall ecological environment quality has been improved, and the total discharge of major pollutants has been dramatically reduced. The concentrations of major pollutants such as SO_2 and NO_2 in 168 prefecture-level and above cities decreased compared with those in 2019 (MEEPRC, 2021). At the same time, China's ecological and environmental protection has also faced major challenges, such as the contradiction between economic and social development and ecological and environmental protection. Therefore, reducing environmental pollutant emissions is another crucial objective of China's industrial restructuring strategy. Here, we considered five primary pollutant emissions, namely, SO_2, NO_X, SD, COD, and AN, and the cumulative amounts of them were minimized (see the Eq (6)-(10)).

$$\min\ f_6 = \sum_{t=1}^{T}\sum_{j=1}^{N} si_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{6}$$

$$\min\ f_7=\sum_{t=1}^{T}\sum_{j=1}^{N} ni_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{7}$$

$$\min\ f_8=\sum_{t=1}^{T}\sum_{j=1}^{N} sdi_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{8}$$

$$\min\ f_9=\sum_{t=1}^{T}\sum_{j=1}^{N} codi_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{9}$$

$$\min\ f_{10}=\sum_{t=1}^{T}\sum_{j=1}^{N} ani_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \tag{10}$$

where si_j^t, ni_j^t, sdi_j^t, $codi_j^t$, and ani_j^t were 11×48 parameters, representing SO_2, NO_X, SD, COD, and AN emissions per unit sectoral added value in the *t*-th year, respectively.

3.1.3. Constrains

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

$$x_i^t - \sum_{j=1}^{N} a_{ij}^t x_i^t \geq f_i^t,\ i=1,\cdots,N;\ t=1,\cdots,T \tag{11}$$

b) Sectoral production capacity constraints. To maintain the stability of the economic system, sectoral output capacity should also be considered. Therefore, the outputs of each sector were limited within a certain range compared with the levels in the previous year. Besides, for the whole planning period, the output of each department should not be lower than the initial level.

$$\varphi_1 x_i^{t-1} \leq x_i^t \leq \varphi_2 x_i^{t-1},\ i=1,\cdots,N;\ t=1,\cdots,T \tag{12}$$

$$x_i^t \geq x_i^0,\ i=1,\cdots,N;\ t=1,\cdots,T \tag{13}$$

where φ_2 >1> φ_1. φ_1 and φ_2 were the upper and lower limits of the output growth rate for each sector, respectively. x_i^0 denoted the initial value of outputs in sector *i*.

c) The constraints of minimum annual economic growth. Currently, China is still in the stage of a middle-income country. As a large country with a population of 1.4 billion, setting growth targets is conducive to increasing residents' income. The government proposes that the per capita GDP will reach the level of moderately developed countries by 2035, which means that China's GDP needs to maintain a certain growth rate in the next 15 years. By comprehensively considering the current level of economic growth, the utilization of existing resource elements, and future high-quality development, the expected targets of annual economic growth were set:

$$\sum_{j=1}^{N} x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \ge (1+r_t) \sum_{j=1}^{N} x_j^{t-1} (1-\sum_{i=1}^{N} a_{ij}^t) \tag{14}$$

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

d) The constrain of annual total energy consumption and the total number of employees. The total energy consumption of all sectors cannot be more than the total energy supply for the *t*-th year. The upper limit of total energy consumption was formulated as follows.

$$\sum_{j=1}^{N} ei_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \le \overline{ES}_t \tag{15}$$

$$\sum_{j=1}^{N} li_j^t x_j^t (1-\sum_{i=1}^{N} a_{ij}^t) \le \overline{LS}_t \tag{16}$$

where $\overline{ES}_t$ and $\overline{LS}_t$ were the maximum energy supply and labor supply for the production process in the *t*-th year, respectively.

3.2. Model solving algorithm

3.2.1. Ideal point and payoff matrix

The ideal point method was introduced in this study to reconcile the ten possible conflicting objectives. The ideal point is determined by each single-objective linear programming solution and defined as the utopia solution that achieves the optimum among the entire set of single-objectives. At the center of ideal point method is to find the point closest to the ideal point using the defined model. The ideal point method is widely used in the research of multi-objective decision making because it can avoid the black-boxed operation in the process of solving and the subjectivity of setting weights, and it is simple and easy to operate (Omagari and Higashino, 2018; Wang et al., 2016).

To determine the ideal point, the payoff matrix should be constructed as *PM* as follow, which denotes the value of the *i*-th objective when the *j*-th objective is optimized. The ideal point was identified by the best solution of each objective and located at the diagonal position of the payoff matrix.

$$PM = \begin{bmatrix} \theta_1(x^1) & \theta_2(x^1) & \cdots & \theta_{10}(x^1) \\ \theta_1(x^2) & \theta_2(x^2) & \cdots & \theta_{10}(x^2) \\ \vdots & \vdots & \ddots & \vdots \\ \theta_1(x^{10}) & \theta_2(x^{10}) & \cdots & \theta_{10}(x^{10}) \end{bmatrix} \tag{17}$$

where $\theta_1(x^1)$, $\theta_2(x^2)$, ..., $\theta_{10}(x^{10})$ indicated the maximized GDP, minimized carbon emission, minimized energy consumption, maximized employment, minimized SO_2

emission, minimized NOx emission, minimized SD emission, minimized COD emission, and minimized AN emission, respectively. $x^k (k = 1, 2, \cdots, 10)$ denoted the solutions when the *k*-th objective was optimized. $\theta_l(x^k)$ $(l = 1, 2, \cdots, 10)$ stood for the value of the *l*-th objective when the *k*-th objective was optimized.

3.2.2. Compromise solution

Based on the ideal point and payoff matrix concept, the compromise solution was calculated by minimizing the distance to the ideal point. The distance between the compromise solution and the ideal point was measured by the Minkowski metric, which was denoted as,

$$\min \ d = \sqrt{\sum_m (1-\delta_m(x))^2}, \ m = 1, 2, \cdots, 10 \tag{18}$$

s.t.

$$\delta_m(x) = [\theta_m(x) - \theta_m^{\min}] / (\theta_m^{\max} - \theta_m^{\min}) \tag{19}$$

where $\delta_m(x)$ was the standardized objective function for the *m*-th conflicting objective. $\theta_m^{\min}$ and $\theta_m^{\max}$ represented the minimum and maximum values in the *m*-th column elements of the payoff matrix, respectively. Since the standard formula of the Minkowski metric is used for maximization optimization, the minimizing single-objective model was converted to the maximizing model and the solution. The compromise solution solved by Eq. (18) and (19) combined with the single-objective model was the point closest to the ideal point.

3.3. Data and parameters

The planning period covers 2020-2030. The latest Chinese non-competitive IO table in 2018 with 42 sectors published by the National Bureau of Statistics (NBSC, 2017) was used to derive the IO technical coefficient in this study. According to the assumption that the technical coefficient is unchanged in this study, the IO technical coefficients during 2020-2030 remained the same as these in 2018. In the IO table, the Production and Supply of Electric Power sector was disaggregated into the 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:

a) The sectoral carbon emission coefficients and energy consumption coefficients during 2020-2030 have been estimated according to the historical data and referred to Song et al. (2018). The carbon emission coefficients of sub-divided electricity sectors were calculated by the proportion of carbon emission from thermal power units. The energy consumption coefficients were obtained by the proportion of standard coal consumption for electricity generation. The employment coefficients representing the sectoral labor force needed per unit added value during 2020-2030 were estimated by the trend extrapolation models for each sector according to the values from 2011 to 2019. We first calculate the historical employment intensity from 2010 to 2019 based on the historical data of added value and employment by sector in the China Statistical Yearbook. We then estimate the employment intensity by sector from 2020 to 2030 using trend extrapolation models.

Data on SO_2 emission, NOx emission, SD emission, COD discharge, and AN discharge in the agriculture and manufacturing sectors were obtained from the China Statistical Yearbook. The coefficients of SO_2 emission, NOx emission, SD emission, COD discharge, and AN discharge, representing the emissions per unit added value, were calculated by dividing the emissions by the added value. Then, those coefficients in the planning period were estimated by the trend extrapolation models for each sector according to the values from 2016 to 2019. In addition, coefficients of the pollutant emissions mentioned above in the construction and services sectors and water consumption in all sectors were referred to (Wang et al., 2020).

b) The final demand data were estimated by the trend extrapolation model according to the IO tables during 2002-2017 (NBSC, 2018). All final sectoral demands data were transformed into 2018 constant price.

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

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

e) The maximum energy consumption and labor supply. According to the policy of the Revolution Strategy for Energy Production and Consumption (2016-2030) (NDRCC, 2016) prediction for China's energy for the maximum supply amount (Yu et al., 2018b), the maximum energy consumption in 2020 and 2030 was set to 5.2 and 6 billion tons of standard coal, respectively. 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 (NBSC, 2020).

4. Results and Discussion

4.1. Trade-offs among multiple objectives

The initial single-objective optimization solutions and the corresponding compromise solution are shown in **Figure 1**. According to the distance between the single-objective optimization model and the compromise solutions, the objective of maximizing employment is closest to the compromise solution, which indicates that the target of maximizing employment is relatively easy to achieve and has little improved potential when the total number of workers is limited. Nevertheless, other policy targets, such as minimizing energy consumption and pollutant emissions (SO_2, NOx, SD emissions), conflict with the employment target, especially when the optimization objective is minimizing energy consumption, and the total employment loss is 290 million people compared with the compromise solution. Regarding the objective of maximizing GDP, there is a trade-off between the realization of the economic objective and other objectives. The GDP obtained by the compromise solution is between the economy-dominated scenario and the scenarios dominated by other targets (The goal-dominated scenario in this paper refers to the scenario when a goal is optimized, e.g., pursuing the maximization of GDP). Another notable result is that the employment-dominated scenario do not play a significant role in promoting economic development.

Compared with the compromise solution, increased carbon emission and energy consumption in the employment-dominated and economy-dominated scenarios indicates that the increased employment and economic outputs come at the expense of greater energy consumption and more carbon emissions. It is worthwhile to note that the energy-saving-dominated scenario is conducive to the realization of minimizing carbon emissions. In contrast, the low-carbon-dominated scenario can not optimize the target of minimizing energy consumption with a higher energy consumption of 4.75 billion tce (tons of standard coal equivalent). The carbon emissions in the COD and AN reduction-dominated scenarios are off its target, and the energy consumption in the SO_2, SD, COD, and AN reduction-dominated scenarios is also off its target, indicating that there are trade-off effects among these policy targets. In comparison, the targets of minimizing carbon emission and energy consumption in the water conservation and NOx reduction-dominated scenarios can be achieved.

As for the target of minimizing water consumption, it also can be achieved in the energy-saving and NOx reduction-dominated scenarios, implying that the realization of energy-saving and NOx emission reduction targets has a synergistic effect on water resource conservation. While the realization of maximizing employment and minimizing carbon emission, SD, COD, and AN emissions has a reverse effect on saving water resources. Regarding to the targets of minimizing other pollutant emissions, increased SO_2, NOx, SD, COD, and AN emissions in the economy and employment-dominated scenarios indicate that the economic growth and increased employment are also at the expense of greater major pollutant emissions. Another notable result is that the realization of minimizing carbon emissions leads to more emissions of SO_2, NOx, and SD compared to the compromise solution. Due to this trade-off effect, SO_2, NOx, and SD emissions in the low-carbon-dominated scenario are off their targets. Moreover, there are synergy effects among SO_2, COD, and SD emissions, as the reduction targets of these three pollutants can be optimized under the other two dominant scenarios.

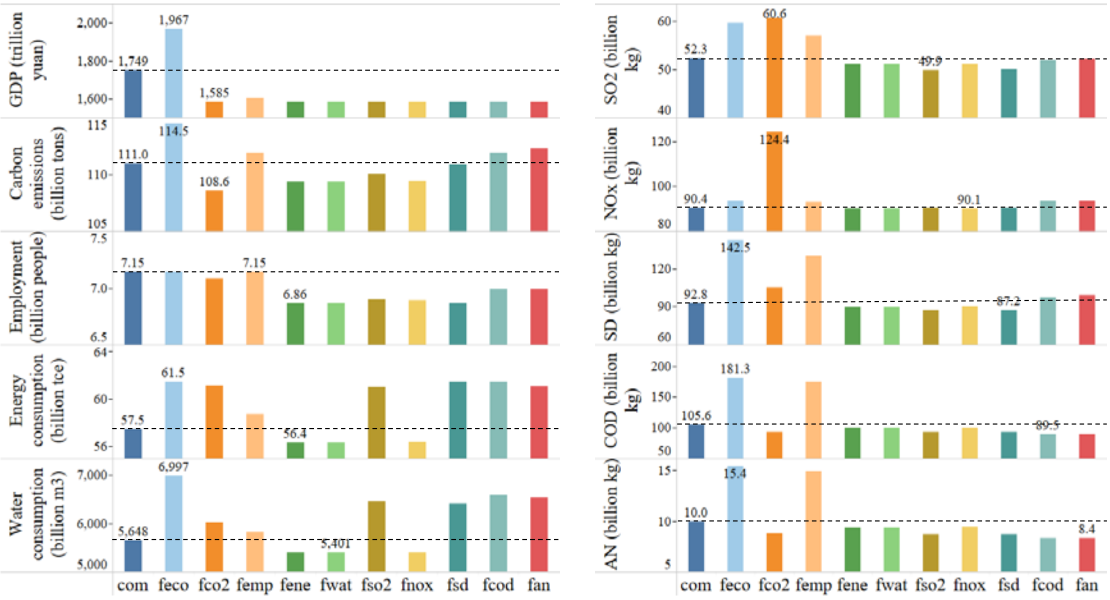

Figure 1. Comparison between compromise solution and single-objective optimization solutions (com, feco, fco2, femp, fene, fwat, fso2, fnox, fsd, fcod, and fan represent the scenarios dominated by compromise solution, maximizing economic growth, minimizing carbon emissions, maximizing employment, and minimizing energy consumption, water consumption, SO_2, NOx, SD, COD, and AN emissions, respectively)

4.2. The realization of multiple objectives

4.2.1. Changes in economic growth and employment

The GDP will increase from 112 trillion yuan in 2020 to 261 trillion yuan, and the average annual GDP growth rate is 8.9% in the economy-dominated scenario, after industry restructuring, as shown in **Figure 2(a)**. The realization of other objectives curbs the realization of the goal of economic growth with a minimum annual GDP growth rate of 5%. Due to the limited number of employees, the GDP growth in the employment-dominated scenario is not significant, i.e., 192.5 trillion yuan higher than in other scenarios. The difference between the GDP in the most advantageous optimization scenario and the most disadvantageous scenario is 382.6 trillion yuan, indicating that the maximum cumulative GDP potential will reach the level.

The change in employment during 2020-2030 is demonstrated in **Figure 2(c)**. According to the figure, the maximum cumulative employment potential is 280 million people. The total employment will increase from 577.5 million people in 2020 to 674.8 million people in 2030, and the cumulative employment is 7.15 billion people under the employment and economy-dominated scenarios. In contrast, the cumulative employment is 6.86 billion people in the energy-saving, water-saving, and SD emission reduction-dominated scenarios. This finding is primarily attributable to the optimization of industrial structure; emissions reduction and resources conservation and maximization of employment should be considered.

4.2.2. The realization of the carbon emission peak and energy-saving

Figures 2(b) and **(d)** show the realization of minimizing carbon emissions and energy consumption in the planning period of 2020-2030. The trade-offs effects among multiple objectives are reflected in carbon emission and energy consumption. Specifically, the cumulative maximum potential of carbon emission reduction and energy consumption saving are 5.86 billion tons and 5.12 billion tce. When the policy target is dominated by carbon emission reduction, the carbon emissions will increase from 9.79 billion tons in 2020 to 9.97 tons, which is achieved at the cost of compromising massive economic output and increasing the emission of other pollutants, such as SO_2 and NOx. In other optimization scenarios, carbon emissions are higher than this optimal solution. Typically, the carbon emissions will surge to 11.13 billion tons in 2030 in the economy-dominated scenario. In other optimization scenarios, such as minimizing COD, AN emissions, and maximizing employment, carbon emissions fluctuate from 9.79 to 10.5 billion tons. The most advantageous scenarios for carbon emission reduction are energy-saving and water-saving-dominated scenarios, in which the cumulative carbon emission is only 773 million tons more than the optimal scenario. This finding indicates the implementation of energy-saving and water-saving measures will be beneficial to carbon emission reduction; however, the realization of minimizing COD and AN emissions and maximizing employment has an interference effect on carbon emission reduction.

Regarding minimizing energy consumption, a considerable potential for energy saving can be observed in **Figure 2(d)**. According to the proposed model results, the energy consumption will increase from 5.08 billion tce in 2020 to 5.17 billion tce in 2030, a slight increase which is at the expense of other targets. Maximization of economy and minimization of SD and COD emissions has the greatest resistance to the realization of energy-saving goals, driving the cumulative energy consumption increase to 61.5 billion tce, and the energy consumption is 6 billion tce in 2030 in the economy, SO_2, SD, and COD emission reduction-dominate scenarios. Moreover, the goals of minimizing water consumption and NOx emission have synergistic effects on energy conservation, driving the cumulative energy consumption increase to 56.4 billion tce. It is worth noting that the energy consumption when maximizing employment is less than that when optimizing other objectives, while the minimization of carbon emission plays a minor role in energy conservation. The findings indicate that adjusting the economic structure for increasing employment is more beneficial to saving energy consumption than reducing carbon emission.

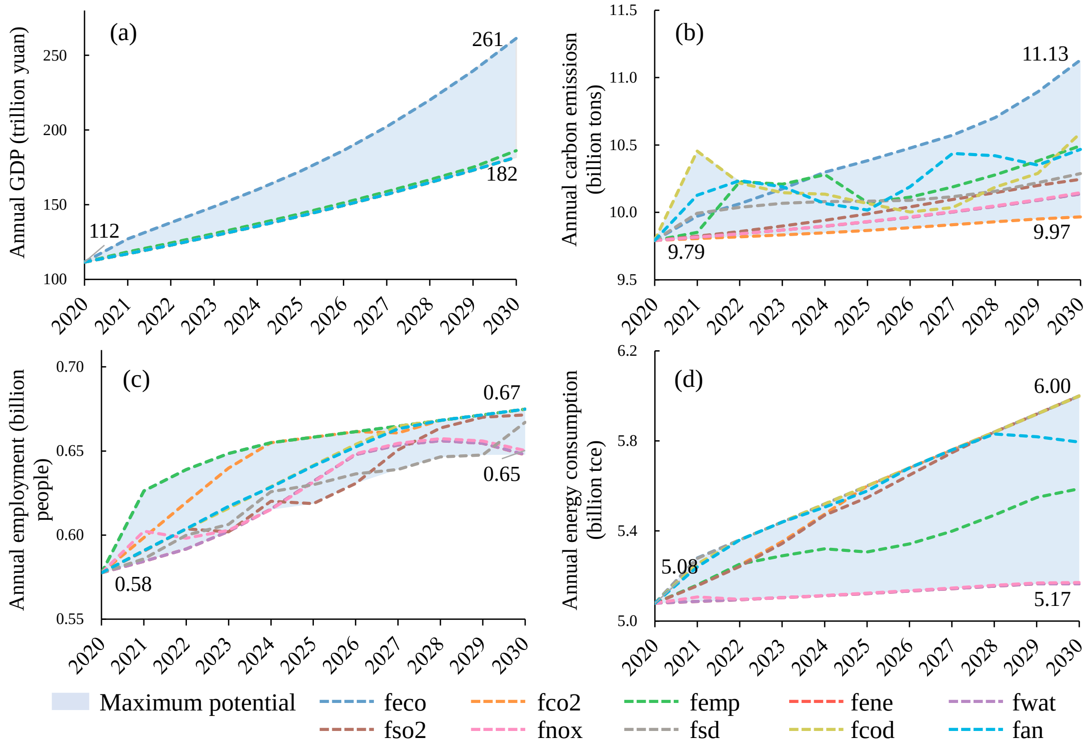

Figure 2. The realization of maximizing economic growth and employment, and minimizing carbon emission and energy consumption when optimizing every single objective during 2020-2030 (feco, fco2, femp, fene, fwat, fso2, fnox, fsd, fcod, and fan represent the scenarios dominated by maximizing economic growth, minimizing carbon emissions, maximizing employment, and minimizing energy consumption, water consumption, SO_2, NOx, SD, COD, and AN emissions, respectively)

4.2.3. Targets of water-saving and pollutants reduction

For the objectives of minimizing water consumption and other pollutant emissions (**Figure 3**), the objective with the greatest optimization potential is minimizing water consumption, with a maximum potential of 1596 billion m^3. Generally, the water consumption will decrease in the planning period when the policy targets are dominated by minimizing energy consumption, water consumption, and NOx reduction and maximizing employment. In contrast, it will increase yearly in the economy-dominated scenario, from 581 billion m3 in 2020 to 658 billion m3. When in other scenarios, such as the low-carbon-dominated scenario, the water consumption will experience a process of decreasing first and then increasing in the planning period. The water resource consumption increase is the most obvious under the SO_2 and SD reduction-dominated scenarios.

Among other pollutant emissions, the target of minimizing SO_2 emission possesses a small optimization potential of 10.7 billion kg. Generally, the SO_2 emission will decreases yearly in all optimization scenarios, from 6.41 billion kg in 2020 to 3.42-5.41 billion kg in 2030. Specifically, it will decline the fastest in the SO_2, SD reduction, water, and energy-saving-dominated optimization scenarios. At the same time, there is a slight decline in SO_2 emission in the optimization scenarios of maximizing economic growth, minimizing carbon emission, and maximizing employment. A relatively large optimization potential exists in the optimization scenarios of minimizing NOx emission, and the emission reduction gap mainly existed between the low-carbon dominated scenario and other scenarios. In the low-carbon-dominated scenario, the NOx emission will increase from 9.28 billion kg in 2020 to 13.4 billion kg in 2030, while it will decrease year by year to 7.75-8.31 billion kg in other scenarios.

The same pattern in the realization paths of minimizing SD, COD, and AN emissions is observed. They will increase in the economy and employment-dominated scenarios and decreased in other scenarios in the planning period. SD, COD, and AN emissions possess the maximum optimization potentials of 92.8 billion kg, 105.6 billion kg, and 9.98 billion kg, respectively. In the economy-dominated scenario, the emissions of SD and COD will increase from 8.68 billion kg and 10.04 billion kg in 2020 to 18.77 billion kg and 25.72 billion kg in 2030, respectively. While the AN emission will decrease from 1.31 billion kg in 2020 to 1.2 billion kg in 2023 and then increase to 1.98 billion kg in 2030.

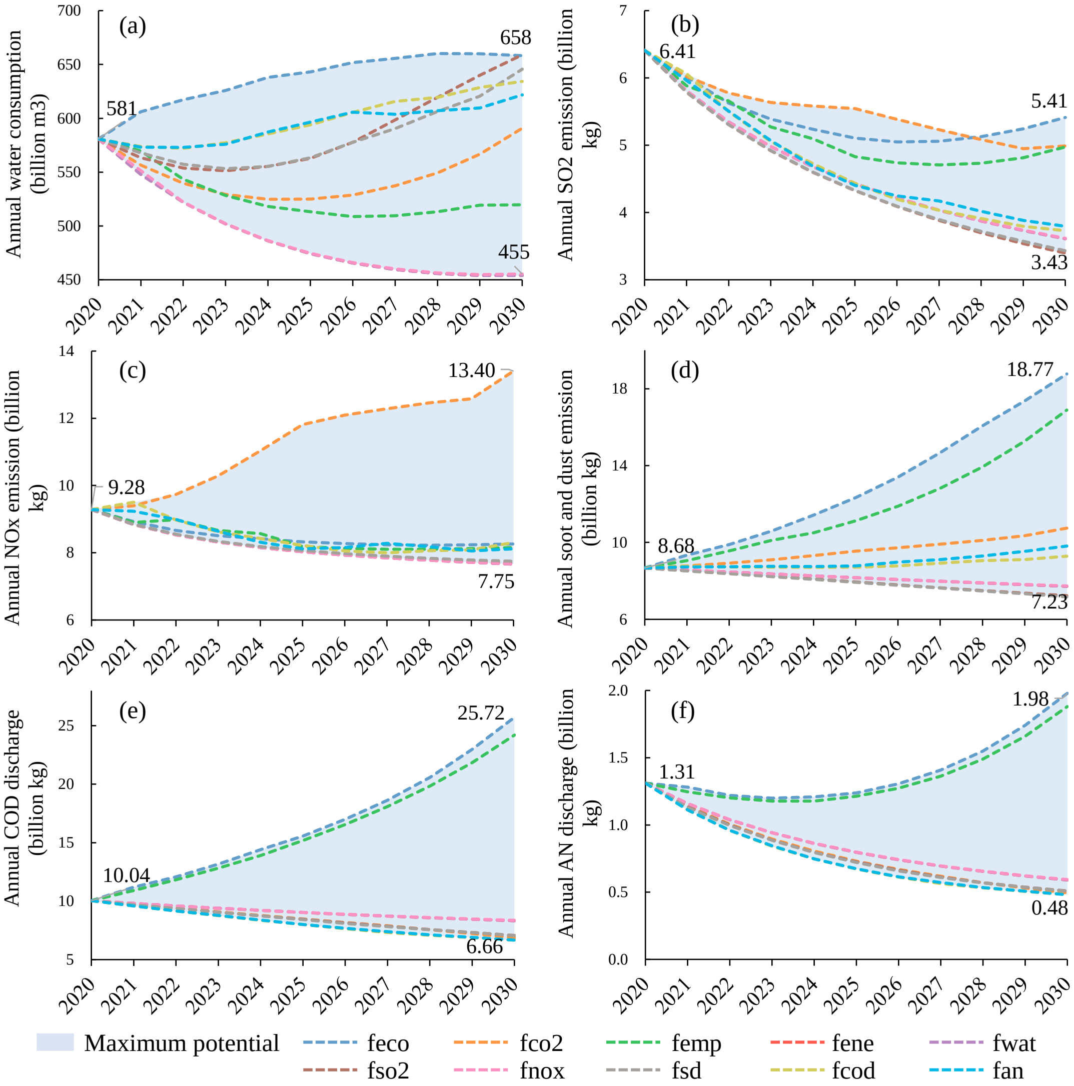

Figure 3. The realization of minimizing water consumption, SO_2, NOx, SD, COD, and AN emissions when optimizing every single objective during 2020-2030

4.3. Sectoral trade-offs among multiple objectives

The synergy and trade-offs among multiple policy objectives can be reflected at the sectoral level. Thus more detailed analysis results can be obtained, as shown in **Figure 4**. When comparing the sectoral outputs changes in single-objective optimization scenarios with the compromise scenario, the changes in sectoral outputs in various scenarios can be observed. In the economy and employment-dominated scenarios, the output growth rate of the S1 (Agriculture), S21 (Instruments and Apparatuses), and S33 (Construction) sectors are higher. While the output growth rate of the S45 (Education) is lower in the economy-dominated scenario and output growth rates of the S26 (Hydropower), S27 (Wind Power), S29 (Nuclear power), S30 (Solar power), and S39 (Real Estate) are lower in the employment-dominated scenario. This finding indicates that the increase of outputs in the S1, S21, and S33 sectors is more beneficial to maximizing economic growth and employment than other goals. There is also a generally higher growth rate of sectoral outputs reflected in the employment-dominated scenario, which indicates that the employment-dominated scenario is more conducive to the balanced development of most sectors.

The output growth rate of the S24 (Electricity Transmission and Distribution), S31 (Production and Supply of Gas), and S33 sectors are higher in the low-carbon-dominated scenario than in the compromise scenario, indicating that development in these sectors is beneficial to the realization of minimizing carbon emission. However, the S38 (Finance), S39, and S45 have lower output growth rates in the low-carbon-dominated scenario. It is worthwhile to notable that the sectoral outputs growth in energy and water-saving-dominated scenarios is closer to that in the compromise scenario, especially for the S45 and S43 (Water Conservancy, Environment, and Public Facilities Management) sectors. The exceptions are that S38 had no increase in its output in the energy-saving-dominated scenario, while S45 and S39 have slower growth in the water-saving-dominated scenario.

With regards to the targets of minimizing other pollutant emissions, the output growth rates of the S8 (Garments, Fiber, Leather, Furs, Down and Related Product), S17 (Equipment for Special Purposes), S18 (Transportation Equipment), S19 (Electronic and Telecommunications Equipment), and S20 (Communication Equipment, Computers, and Other Electronic Equipment) are higher in the SO_2 emission reduction dominated scenario than in the compromise scenario, whereas the S38, S45, and S39 have lower growth rates in their outputs. The results also show that the development of S19, S20, and S21 sectors is also more conducive to minimizing NO_X and SD emissions, while the S39 and S45 have lower growth rates in their outputs in NO_X, SD, COD, and AN emissions reduction dominated scenarios. Moreover, the output growth in S33 is also conducive to the realization of minimizing COD and AN emissions. These findings indicate that other pollutant emissions in some technology-intensive manufacturing sectors, such as S19, S20, and S21, have been reduced significantly. The S8 sector, a traditional manufacturing sector, and S17 (Equipment for Special Purposes) can achieve remarkable SO_2 and SD emissions reduction achievements.

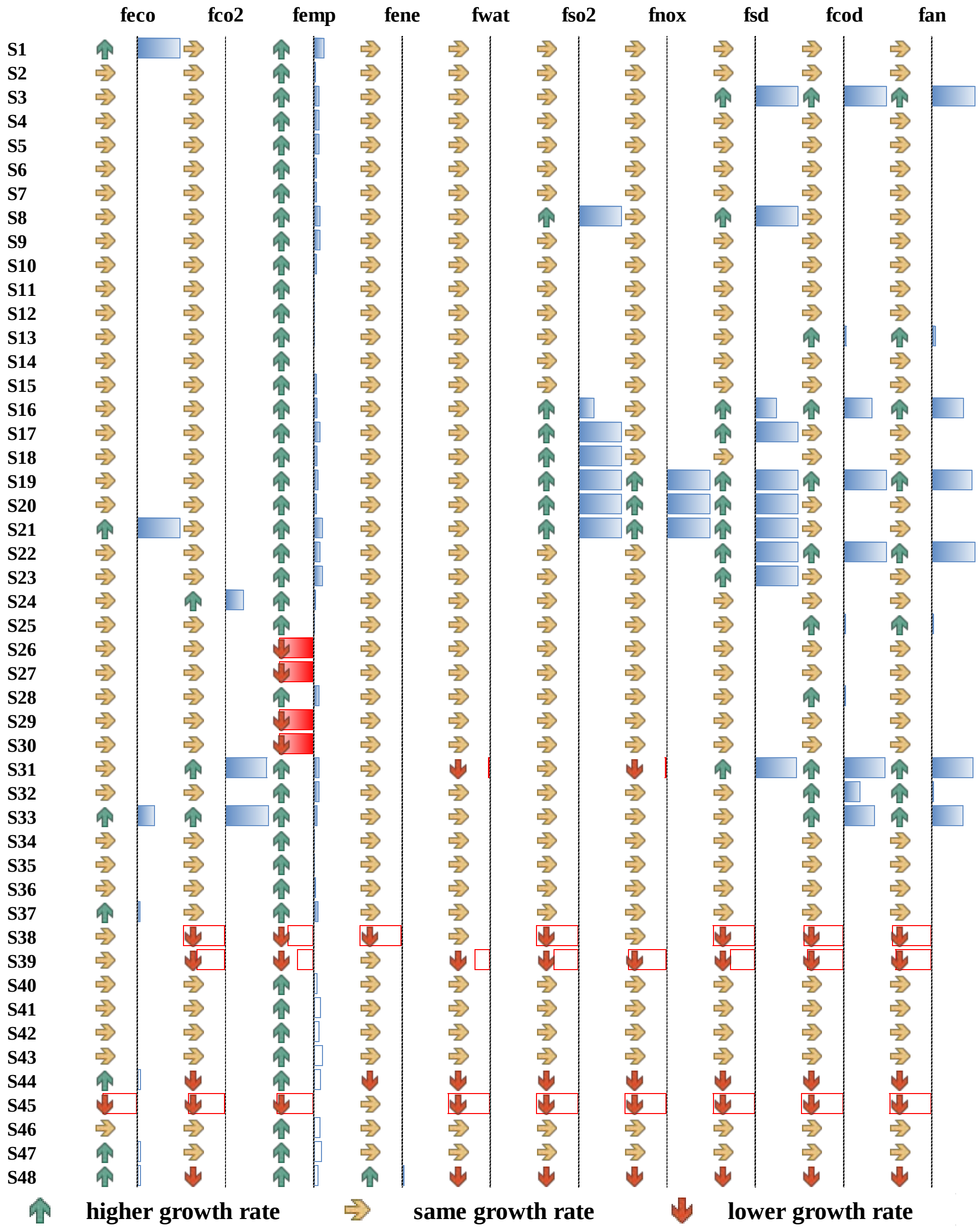

Figure 4. Comparison of the growth rate of sectoral outputs between single objective optimization solutions and the compromise solution from 2020 to 2030

4.4. Compromise solution

4.4.1. Realization of multiple objectives

The complete structure should be a trade-off among the conflicting objectives. Based on the ideal point and payoff matrix, the concept compromise solution is the closest point to the ideal point, representing the trade-off solution after comprehensively considering various objectives. **Figure 5** demonstrates the realization of multiple objectives of a compromise solution. With the industrial restructuring, the GDP, employment, carbon emission, and energy consumption will increase 96.1%, 7.2%, 16.8%, 16.8%, and 6.3%, respectively. Other targets will decrease in the planning period; for example, the AN emission amount decrease by 49.3%. It is worth noting that the number of employees will reach the maximum labor supply, and the amount of energy consumption is lower than the maximum energy supply in the planning period. The carbon emissions will slowly rise to 10.5 billion tons in 2030, close to the peak point of carbon emission in several studies (Li et al., 2016; Xu et al., 2019, 2020). The results for carbon emissions and energy consumption are similar to findings in existing studies addressing net-zero emission issues in China. For example, our results share the same net emissions trajectory as in the NDC (China's nationally determined contribution) scenario proposed by Zhang et al. (2021a). Xu et al. (2020) show that under the PE (planned energy structure) scenario, China's predicted carbon emissions will peak in 2030, and the value is 10.69 billion tons. Moreover, one study (He et al., 2022) finds that China's primary energy consumption in 2030 is projected to be 5.8 billion tce under energy-target scenarios.

To vigorously promote energy conservation and emission reduction and further strengthen pollution prevention and control, China's 14th FYP sets the following goals for its environmental sustainability: by 2025, China will reduce, from its 2020 levels, energy intensity, carbon intensity, COD, AN, and NOx by respectively, more than 13.5%, 18%, 8%, 8%, and 10 %. Our results of the compromise solution indicate that energy intensity and carbon emissions intensity will decrease by nearly 26% in 2020-2025 –we also find a similar reduction in 2025-2030 (listed in **Table A2**). Our results reflect that both energy intensity and carbon emission intensity can reach and even exceed the targets set by the national government through the adjustment of industrial structure. Our results also indicate that the reduction of AN and NOx can reach the national target, but the reduction of COD can not reach the expected target during the 14th FYP period. Thus, it is necessary to further strengthen the control of COD source discharge in agricultural and industrial sectors during the 14th and 15th FYP period.

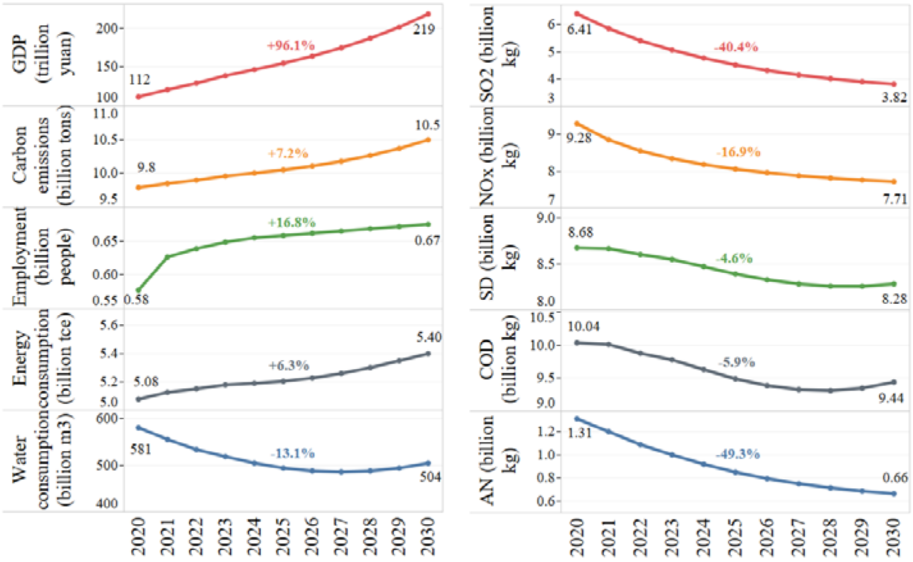

Figure 5. The realization of maximizing GDP, minimizing carbon emissions, maximizing employment, minimizing energy and water consumption, and minimizing SO_2, NOx, SD, COD, and AN emissions under the compromise solution during 2020-2030

4.4.2. Structural changes in sectoral output

China's economy has experienced a structural transition from the dominance of energy-based secondary industry to knowledge and technology-based tertiary sector in the optimization process of multiple policy targets, including economy, employment, energy consumption, and environmental pollutant emissions. According to the optimization results of the compromise solution, the proportion evolution of six industries, including agriculture, mining, manufacturing, electricity, heat, and water, construction, and services sectors, as shown in **Figure 6(a)**. The proportion of manufacturing sectors' total outputs to total economic outputs will decrease significantly, from 40% in 2020 to 25% in 2030. At the same time, the proportion of services industries' total outputs will increase gradually, from 38% in 2020 to 60 % in 2030. The proportions of agriculture, mining, and construction industries' total outputs will decrease slightly. And the electricity, heat, and water industry remain almost constant in its proportion during this period, mainly because low-carbon energy power generation replaces most coal-fired and gas-fired power generation.

In 2030, the output proportion of nearly half sectors of 48 sectors shows significant changes compared to those in 2020 after searching the compromise solution. According to the results, the output proportions of S38 (Finance), S39 (Real Estate), and S45 (Education) increase significantly, whereas the output proportions of S33

(Construction), S34 (Wholesale and Retail Trade), S12 (Chemical Products), S14 (Smelting and Pressing of Metals), S20 (Communication Equipment, Computers, and Other Electronic Equipment), and S35 (Transport, Storage, Postal & Telecommunications Services) decline gradually. There are minor changes in the output proportion of other sectors mainly because the output of those industries account for a relatively small proportion of the overall economic output.

From the relative change of industrial output proportion, the output proportions of electricity sectors, such as S26 (Hydropower), S27 (Wind Power), S29 (Nuclear power), and S30 (Solar power) will increase rapidly. The proportion evolution of six electricity sectors, including coal-fired power, hydropower, wind power, natural gas power, nuclear power, and solar power sectors, is shown in **Figure 6(b)**. As we can see, the dominant position of coal-fired power in 2020 will gradually disappearing with a sharp decline in its output proportion from 65% in 2020 to 26% in 2030. Instead, the renewable energy power generation industry will developing rapidly. Most noticeably, the output proportion of the hydropower sector will increase from 13% in 2020 to 32% in 2030, followed by the wind power sector, of which the output proportion will increase from 7% in 2020 to 18%. The output proportion of low-carbon electricity sectors will increase from 29% in 2020 to 72% in 2030.

These changes demonstrate that under the comprehensive consideration of targets on economic growth, employment, carbon emission, energy and water conservation, and other environmental pollutant emissions, certain energy-intensive and emissions-intensive sectors will be inhibited to a certain extent, and the output in some services sectors and low-carbon electricity sectors will increase expeditiously. However, there are exceptions; for example, the output of S19 (Electronic and Telecommunications Equipment), knowledge and technology-based sector, will have a certain degree of decline. This finding indicates that high energy consumption and high emissions still exist in most China’s manufacturing industries. Therefore, to realize the comprehensive government of multiple policy targets on the economy, employment, and environment, the manufacturing sectors must maintain sustainable green development.

The electricity generation patterns obtained in this study are similar to studies that use long-term models to predict the power generation structure. For example, one study demonstrated that in 2030, the installed capacity of renewable energy would account for 70% of the total capacity under the PEAK20 and PEAK25 scenarios (Zhang and Chen, 2022). Overall, however, the proportion of electricity generated from renewable sources in this study will be higher than that projected by other long-term studies, e.g., studies by (Kang et al., 2020b; Yang et al., 2021b). The main reasons for this difference may be as follows. First, this paper discusses emissions reduction and energy conservation from industrial structure optimization, while other studies focus on minimizing the total cost of energy technologies or other systems. Second, while other studies consider only one goal, in this study we consider ten sustainability goals, i.e., goals covering economic, social, carbon emissions, energy, and other environmental indicators simultaneously. Finally, the output of the power sector in this paper is different from the generating capacity considered by other studies.

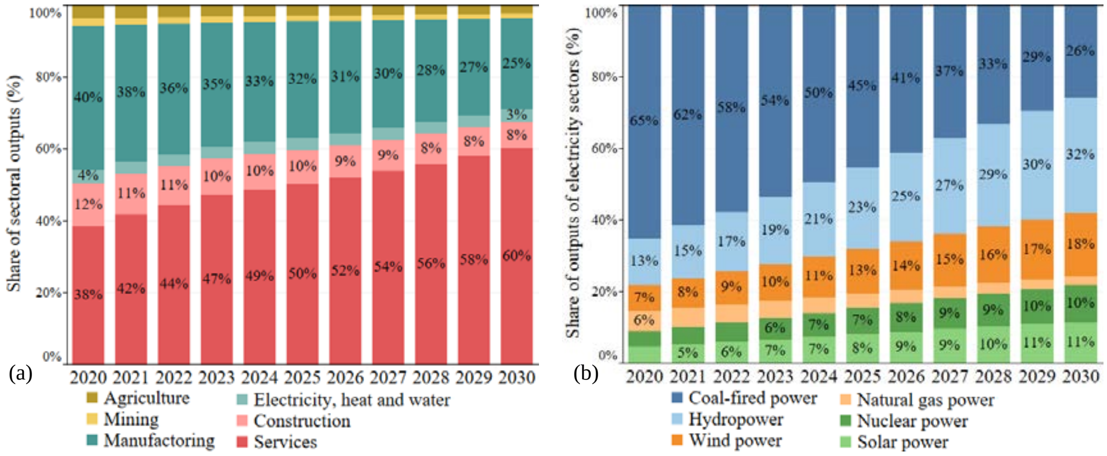

Figure 6. Changes in the output structures of six major industries and electricity sectors under the compromise solution during 2020-2030

5. Conclusion and Policy Implications

5.1. Conclusions

Previous studies have provided strong evidence of the role of industrial structure adjustment in reducing emissions and energy consumption; however, the literature is not well advanced on improving the industrial production structure to balance competing policy targets need. Therefore, we proposed a multi-objective optimization model based on IO analysis to investigate the synergy and trade-offs among multiple objectives, including maximizing GDP and employment and minimizing carbon emission, energy consumption, water consumption, SO_2, NOx, SD, COD, and AN emissions. According to the optimization results, the following conclusions are obtained.

a) Synergy and trade-offs among multiple objectives. The increased employment and economic outputs are at the expense of other objectives, such as greater energy consumption and carbon emissions. The policy targets of minimizing the energy consumption and pollutant emissions (SO_2, NOx, SD emissions) conflict with maximizing employment, especially when the optimization objective is minimizing energy consumption, and the total employment loss is 290 million people compared with the compromise solution. Implementing energy-saving and water-saving measures will be beneficial to carbon emission reduction; however, the realization of minimizing the COD and AN emissions and maximizing employment interferes with the target of reducing carbon emissions. The maximization of the economy and the minimization of SD and COD emissions have the greatest resistance to minimizing energy consumption, while the goals of minimizing the water consumption and NOx emission have synergistic effects on energy conservation. Furthermore, there is a synergy effect among the goals of minimizing water consumption, energy consumption, and NOx emission reduction. However, the emissions reduction of SO_2, NOx, and SD will be hindered by the goal of minimizing carbon emissions.

b) Realization of each policy target. The compromise solution provides a relatively optimal industrial restructuring pathway for the consideration of policy consistency among various policy targets. Accordingly, the GDP, employment, carbon emission, and energy consumption will increase, respectively, 96.1%, 7.2%, 16.8%, 16.8%, and 6.3% through the industrial restructuring, while pollutant emissions will decrease during the planning period. Further, the objective with the greatest optimization potential is minimizing water resource consumption, with a maximum water-saving potential of 1,596 billion m^3. Our results also reveal that despite comprehensive consideration of multiple policy objectives, the carbon emission of China's industrial sectors can be controlled by 10.5 billion tons in 2030 through industrial restructuring, which is regarded as the peak point of carbon emission by several studies.

c) Policy preference to achieve various objectives synergistically. The sectoral outputs growth in energy and water-saving-dominated scenarios is closer to the compromise scenario, which indicates that these two scenarios are the most satisfactory optimal pathways to adjust the industrial production structure. There is also a generally higher growth rate of sectoral outputs reflected in the employment-dominated scenario, implying that the employment-dominated scenario is more conducive to the balanced development of most sectors. Therefore, to achieve the coordinated development of multiple national targets, the direction and strategy of industrial structure adjustment with energy and water conservation and full employment as the leading policy priorities deserve special attention.

5.2. Policy implications

The period 2020-2030 is the critical stage for China to reach its carbon peak and mobilize towards achieving the ambitious goal of carbon neutrality by 2060. Therefore, to realize the goals of carbon emission, environmental pollutants, and energy consumption reduction while maintaining economic development and full employment through industrial restructuring, the following policy implications on China's developments during the recent 14th and 15th FYPs are proposed.

First, to achieve a comprehensive green transformation in economic and social development, not only emissions reduction and resources conservation but also full employment should be considered during the 14th and 15th FYP periods. It is highly recommended that the direction and strategy of industrial structure adjustment with energy and water conservation are the leading policy priorities because the sectoral outputs growth in energy and water-saving-dominated scenarios are closer to the compromise scenario. However, when the policy goal is dominated by energy conservation, it will lead to the largest reduction in social employment than other scenarios. Although some studies have shown that in the transition to net-zero, the employment in the clean energy sector will increase rapidly (IEA, 2021), the skill sets required for clean energy jobs are different from the traditional energy jobs, which may prevent workers from naturally easing into clean energy jobs, especially for China, a country heavily dependent on fossil energy production and consumption. Therefore, the Chinese government should consider risks to employment levels in achieving energy conservation and would need to devote resources to training and facilitating new opportunities for its workforce in the emerging economic landscape.

Second, the Chinese government should deal with the trade-off between realizing carbon emission reduction targets and energy conservation, SO_2, NOx, and SD emissions reduction targets by reducing energy consumption and promoting cleaner production in critical sectors. Developing renewable energies and promoting electrification in transport and industry sectors will maximize the synergy between the carbon reduction goal and air quality. Special attention should also be given to the construction sector, where the massive energy consumption, SO_2, NOx, and SD emissions must be further reduced. The industrial sector is an essential source of pollutant generation and discharge, so it is imperative to comprehensively strengthen cleaner production approaches in the industrial sector. The synergistic effect of pollution reduction and carbon reduction can be strengthened by improving the efficient utilization of resources and energy and improving the production process with high-emissions technologies. In this avenue, it is necessary to formulate a series of regulations and policies to reduce pollution and carbon emissions in industries with high emissions, such as the thermal power, steel, coal, and petrochemical industries. Furthermore, it is essential to promote a shift from focusing on end-of-pipe treatment to source prevention and treatment among the above industrial sectors.

Third, the continuous adjustment of industrial structure should be conducted to balance multiple national goals involving economic growth, employment, energy, water, and emissions during the 14th and 15th FYP period. The requirement of “keeping the proportion of manufacturing stable” is put forward in the 14th FYP, which indicates that Chinese policymakers attach great importance to the high-quality and sustainable development of the manufacturing industry. We suggest that government support the expansion of high-end manufacturing and modern service industries, e.g., e-commerce and modern logistics, by guiding investments, adjusting taxation and market regulations, and accelerating the transformation and upgrade of traditional industries. For the comprehensive governance of multiple targets, actively developing renewable energy power generation, e.g., wind and solar power; technology and knowledge-intensive manufacturing sectors; and some service sectors, e.g., finance, should be prioritized. There are substantive trade-offs among multiple policy objectives caused by the industrial structure adjustment strategy. This will help establish a long-term mechanism for industrial structure adjustment in line with the national industrial development trend and contribute to the coordinated realization of multiple policy objectives.

There are some limitations to this study. Firstly, due to the lack of recent official statistical information, the IO 2018 system was utilized, and the technical coefficient matrix is regarded as constant over time. Since the economic system in China will be possibly different from 2020 to 2030, the inter-relationships among sectors can also be different, leading 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. Secondly, the emissions coefficients in this study are based on activity levels, which may oversimplify the mechanism between energy consumption and environmental emissions.

The incorporation of uncertainty treatment in future developments of this model will be useful to provide robust conclusions, i.e., unveiling those policies which reveal more immunity to uncertain sources, e.g., emission estimates, electricity generation mix, and economic projections. Furthermore, the methodology of linking energy consumption with pollutant emissions should be further improved. Towards this end, technology-based energy systems and pollutant emissions modeling are important potential future approaches.

Acknowledgments

The authors would like to acknowledge the financial support of the National Natural Science Foundation of China (72074077, 71704055, 71961137012, 72140006, 72131007).

References

Alimujiang A., Jiang P. 2020. Synergy and co-benefits of reducing co2 and air pollutant emissions by promoting electric vehicles—a case of shanghai. Energy for Sustainable Development, 55, 181-189. doi:https://doi.org/10.1016/j.esd.2020.02.005

Arvanitopoulos T., Agnolucci P. 2020. The long-term effect of renewable electricity on employment in the united kingdom. Renewable and Sustainable Energy Reviews, 134, 110322. doi:https://doi.org/10.1016/j.rser.2020.110322

Cao C., Cui X., Cai W., et al. 2019. Incorporating health co-benefits into regional carbon emission reduction policy making: A case study of china’s power sector. Applied Energy, 253, 113498. doi:https://doi.org/10.1016/j.apenergy.2019.113498

Cao J., Ho M.S., Jorgenson D., 2012. An integrated assessment of the economic costs and environmental benefits of pollution and carbon control, In: Aoki M., Wu J. (Eds), The chinese economy: A new transition. Palgrave Macmillan UK, London; 2012. pp. 231-256.

Chen W., Wu S., Lei Y., et al. 2018. Virtual water export and import in china’s foreign trade: A quantification using input-output tables of china from 2000 to 2012. Resources, Conservation and Recycling, 132, 278-290. doi:https://doi.org/10.1016/j.resconrec.2017.02.017

Cheng J., Tong D., Zhang Q., et al. 2021a. Pathways of china's pm2.5 air quality 2015–2060 in the context of carbon neutrality. National Science Review. doi:10.1093/nsr/nwab078

Cheng Y.-S., Li R., Woo C.-K. 2021b. Regional energy-growth nexus and energy conservation policy in china. Energy, 217, 119414. doi:https://doi.org/10.1016/j.energy.2020.119414

Dell’Anna F. 2021. Green jobs and energy efficiency as strategies for economic growth and the reduction of environmental impacts. Energy Policy, 149, 112031. doi:https://doi.org/10.1016/j.enpol.2020.112031

Dissanayake S., Mahadevan R., Asafu-Adjaye J. 2020. Evaluating the efficiency of carbon emissions policies in a large emitting developing country. Energy Policy, 136, 111080. doi:https://doi.org/10.1016/j.enpol.2019.111080

Dong H., Dai H., Dong L., et al. 2015a. Pursuing air pollutant co-benefits of co2 mitigation in china: A provincial leveled analysis. Applied Energy, 144, 165-174. doi:https://doi.org/10.1016/j.apenergy.2015.02.020

Dong H.J., Dai H.C., Dong L., et al. 2015b. Pursuing air pollutant co-benefits of co2 mitigation in china: A provincial leveled analysis. Applied Energy, 144, 165-174. doi:10.1016/j.apenergy.2015.02.020

Dong K. 2009. The dynamic optimization model of industrial structure with energy-saving and emission-reducing constraint. Journal of Sustainable Development, 1. doi:10.5539/jsd.v1n2p27

Driscoll C.T., Buonocore J.J., Levy J.I., et al. 2015. Us power plant carbon standards and clean air and health co-benefits. Nature Climate Change, 5, 535-540. doi:10.1038/nclimate2598

Du L., Zhao H., Tang H., et al. 2021. Analysis of the synergistic effects of air pollutant emission reduction and carbon emissions at coal-fired power plants in china. Environmental Progress & Sustainable Energy, 40, e13630. doi:https://doi.org/10.1002/ep.13630

FAO, 2014. The water-energy-food nexus a new approach in support of food security and sustainable agriculture, in: 5.7.20 (Ed.).

Feng X.-Z., Lugovoy O., Qin H. 2018. Co-controlling co2 and nox emission in china's cement industry: An optimal development pathway study. Advances in Climate Change Research, 9, 34-42. doi:https://doi.org/10.1016/j.accre.2018.02.004

Füllemann Y., Moreau V., Vielle M., et al. 2020. Hire fast, fire slow: The employment benefits of energy transitions. Economic Systems Research, 32, 202-220. doi:10.1080/09535314.2019.1695584

Guo X., Lu C.-C., Lee J.-H., et al. 2017. Applying the dynamic dea model to evaluate the energy efficiency of oecd countries and china. Energy, 134, 392-399. doi:https://doi.org/10.1016/j.energy.2017.06.040

Guo Y., Chen B., Li Y., et al. 2022. The co-benefits of clean air and low-carbon policies on heavy metal emission reductions from coal-fired power plants in china. Resources, Conservation and Recycling, 181, 106258. doi:https://doi.org/10.1016/j.resconrec.2022.106258

Harlan S.L., Ruddell D.M. 2011. Climate change and health in cities: Impacts of heat and air pollution and potential co-benefits from mitigation and adaptation. Current Opinion in Environmental Sustainability, 3, 126-134. doi:https://doi.org/10.1016/j.cosust.2011.01.001

He L., Wang B., Xu W., et al. 2022. Could china’s long-term low-carbon energy transformation achieve the double dividend effect for the economy and environment? Environmental Science and Pollution Research, 29, 20128-20144. doi:10.1007/s11356-021-17202-1

Huang L., Liu S., Yang Z., et al. 2021. Exploring deep learning for air pollutant emission estimation. Geosci. Model Dev., 14, 4641-4654. doi:10.5194/gmd-14-4641-2021

Huang Y., Matsumoto K.i. 2021. Drivers of the change in carbon dioxide emissions under the progress of urbanization in 30 provinces in china: A decomposition analysis. Journal of Cleaner Production, 322, 129000. doi:https://doi.org/10.1016/j.jclepro.2021.129000

IEA, 2021. Net zero by 2050 - a roadmap for the global energy secto. International Energy Agency.

Jiang L., Zhou H., He S. 2021. Does energy efficiency increase at the expense of output performance: Evidence from manufacturing firms in jiangsu province, china. Energy, 220, 119704. doi:https://doi.org/10.1016/j.energy.2020.119704

Jin G., Fu R., Li Z., et al. 2018. Co2 emissions and poverty alleviation in china: An empirical study based on municipal panel data. Journal of Cleaner Production, 202, 883-891. doi:https://doi.org/10.1016/j.jclepro.2018.08.221

Johnson S., Haney J., Cairone L., et al. 2020. Assessing air quality and public health benefits of new york city’s climate action plans. Environmental Science & Technology, 54, 9804-9813. doi:10.1021/acs.est.0c00694

Kang J., Ng T.S., Su B. 2020a. Optimizing electricity mix for co2 emissions reduction: A robust input-output linear programming model. European Journal of Operational Research, 287, 280-292. doi:https://doi.org/10.1016/j.ejor.2020.04.026

Kang J., Ng T.S., Su B., et al. 2020b. Optimizing the chinese electricity mix for co2 emission reduction: An input–output linear programming model with endogenous capital. Environmental science & technology, 54, 697-706. doi:10.1021/acs.est.9b05199

Kuriyama A., Abe N. 2021. Decarbonisation of the power sector to engender a 'just transition' in japan: Quantifying local employment impacts. Renewable and Sustainable Energy Reviews, 137, 110610. doi:https://doi.org/10.1016/j.rser.2020.110610

Li J., Zhou S., Wei W., et al. 2020a. China's retrofitting measures in coal-fired power plants bring significant mercury-related health benefits. One Earth, 3, 777-787. doi:https://doi.org/10.1016/j.oneear.2020.11.012

Li L., Lei Y., He C., et al. 2016. Prediction on the peak of the co₂ emissions in china using the stirpat model. Advances in Meteorology, 2016, 5213623. doi:10.1155/2016/5213623

Li N., Chen W., Rafaj P., et al. 2019. Air quality improvement co-benefits of low-carbon pathways toward well below the 2 °c climate target in china. Environmental Science & Technology, 53, 5576-5584. doi:10.1021/acs.est.8b06948

Li Q., Wu S., Lei Y., et al. 2021. Evolutionary path and driving forces of inter-industry transfer of co2 emissions in china: Evidence from structural path and decomposition analysis. Science of The Total Environment, 765, 142773. doi:https://doi.org/10.1016/j.scitotenv.2020.142773

Li X., Wang Y., Zhou H., et al. 2020b. Has china's war on pollution reduced employment? Quasi-experimental evidence from the clean air action. Journal of Environmental Management, 260, 109851. doi:https://doi.org/10.1016/j.jenvman.2019.109851

Liang X., Zhang S., Wu Y., et al. 2019. Air quality and health benefits from fleet electrification in china. Nature Sustainability, 2, 962-971. doi:10.1038/s41893-019-0398-8

Liu M., Zhang X., Zhang M., et al. 2021. Influencing factors of carbon emissions in transportation industry based on cd function and lmdi decomposition model: China as an example. Environmental Impact Assessment Review, 90, 106623. doi:https://doi.org/10.1016/j.eiar.2021.106623

Lu Z., Huang L., Liu J., et al. 2019. Carbon dioxide mitigation co-benefit analysis of energy-related measures in the air pollution prevention and control action plan in the jing-jin-ji region of china. Resources, Conservation & Recycling: X, 1, 100006. doi:https://doi.org/10.1016/j.rcrx.2019.100006

MEEPRC, 2021. Bulletin on china's ecological environment in 2020. Ministry of Ecology and Environment of the People's Republic of China.

Mondal M.A.H., Denich M., Vlek P.L.G. 2010. The future choice of technologies and co-benefits of co2 emission reduction in bangladesh power sector. Energy, 35, 4902-4909. doi:https://doi.org/10.1016/j.energy.2010.08.037

MWRPRC, 2021. 2020 china water resources bulletin. Ministry of Water Resources of the People's Republic of China.

Nam K.-M., Waugh C.J., Paltsev S., et al. 2013. Carbon co-benefits of tighter so2 and nox regulations in china. Global Environmental Change, 23, 1648-1661. doi:https://doi.org/10.1016/j.gloenvcha.2013.09.003

NBSC. Input-output tables. China Statistics Press, Beijing: National Bureau of Statistics of China; 2018.

NBSC. China statistical yearbook (2020). China Statistics Press, Beijing: National Bureau of Statistics of China; 2020.

NDRCC, 2016. Revolution strategy for energy production and consumption (2016-2030). National Development and Reform Commission of China.

NDRCC, 2021. The outline of the 14th five-year plan (2021-2025) for national economic and social development and the long-range objectives through the year 2035, in: China N.D.a.R.C.o. (Ed.). People's Publishing House, Beijing.

Oliveira C., Coelho D., Antunes C.H. 2016. Coupling input–output analysis with multiobjective linear programming models for the study of economy–energy–environment–social (e3s) trade-offs: A review. Annals of Operations Research, 247, 471-502. doi:10.1007/s10479-014-1773-5

Omagari H., Higashino S.I. 2018. Provisional-ideal-point-based multi-objective optimization method for drone delivery problem. International Journal of Aeronautical and Space Sciences, 19, 262-277. doi:10.1007/s42405-018-0021-7

Rauner S., Hilaire J., Klein D., et al. 2020. Air quality co-benefits of ratcheting up the ndcs. Climatic Change, 163, 1481-1500. doi:10.1007/s10584-020-02699-1

Schreiner L., Madlener R. 2021. A pathway to green growth? Macroeconomic impacts of power grid infrastructure investments in germany. Energy Policy, 156, 112289. doi:https://doi.org/10.1016/j.enpol.2021.112289

Scovronick N., Budolfson M., Dennig F., et al. 2019. The impact of human health co-benefits on evaluations of global climate policy. Nature Communications, 10, 2095. doi:10.1038/s41467-019-09499-x

Sheng P., Li J., Zhai M., et al. 2020. Coupling of economic growth and reduction in carbon emissions at the efficiency level: Evidence from china. Energy, 213, 118747. doi:https://doi.org/10.1016/j.energy.2020.118747

Shindell D., Smith C.J. 2019. Climate and air-quality benefits of a realistic phase-out of fossil fuels. Nature, 573, 408-411. doi:10.1038/s41586-019-1554-z

Song J., Yang W., Wang S., et al. 2018. Exploring potential pathways towards fossil energy-related ghg emission peak prior to 2030 for china: An integrated input-output simulation model. Journal of Cleaner Production, 178, 688-702. doi:https://doi.org/10.1016/j.jclepro.2018.01.062

Tong D., Cheng J., Liu Y., et al. 2020. Dynamic projection of anthropogenic emissions in china: Methodology and 2015–2050 emission pathways under a range of socio-economic, climate policy, and pollution control scenarios. Atmos. Chem. Phys., 20, 5729-5757. doi:10.5194/acp-20-5729-2020

Wang J., Wang K., Wei Y.-M. 2020. How to balance china’s sustainable development goals through industrial restructuring: A multi-regional input–output optimization of the employment–energy–water–emissions nexus. Environmental Research Letters, 15, 034018. doi:10.1088/1748-9326/ab666a

Wang W., Yang F., Guo Y., et al. 2022. The effects of the promoting the big and quashing the small policy on pollutants from a coal power supply chain perspective. Journal of Environmental Management, 313, 114960. doi:https://doi.org/10.1016/j.jenvman.2022.114960

Wang Y., Zhao N., Jing H., et al. 2016. A novel model of the ideal point method coupled with objective and subjective weighting method for evaluation of surrounding rock stability. Mathematical Problems in Engineering, 2016, 8935156. doi:10.1155/2016/8935156

Wei X., Tong Q., Magill I., et al. 2020. Evaluation of potential co-benefits of air pollution control and climate mitigation policies for china's electricity sector. Energy Economics, 92, 104917. doi:https://doi.org/10.1016/j.eneco.2020.104917

Wu L., Sun L., Qi P., et al. 2021a. Energy endowment, industrial structure upgrading, and co2 emissions in china: Revisiting resource curse in the context of carbon emissions. Resources Policy, 74, 102329. doi:https://doi.org/10.1016/j.resourpol.2021.102329

Wu P., Guo F., Cai B., et al. 2021b. Co-benefits of peaking carbon dioxide emissions on air quality and health, a case of guangzhou, china. Journal of Environmental Management, 282, 111796. doi:https://doi.org/10.1016/j.jenvman.2020.111796

Wu S., Li S., Lei Y., et al. 2020. Temporal changes in china's production and consumption-based co2 emissions and the factors contributing to changes. Energy Economics, 89, 104770. doi:https://doi.org/10.1016/j.eneco.2020.104770

Xu G., Schwarz P., Yang H. 2019. Determining china's co2 emissions peak with a dynamic nonlinear artificial neural network approach and scenario analysis. Energy Policy, 128, 752-762. doi:https://doi.org/10.1016/j.enpol.2019.01.058

Xu G., Schwarz P., Yang H. 2020. Adjusting energy consumption structure to achieve china's co2 emissions peak. Renewable and Sustainable Energy Reviews, 122, 109737. doi:https://doi.org/10.1016/j.rser.2020.109737

Xu M., Qin Z., Zhang S. 2021. Carbon dioxide mitigation co-effect analysis of clean air policies: Lessons and perspectives in china’s beijing–tianjin–hebei region. Environmental Research Letters, 16, 015006. doi:10.1088/1748-9326/abd215

Yang D., Liu D., Huang A., et al. 2021a. Critical transformation pathways and socio-environmental benefits of energy substitution using a leap scenario modeling. Renewable and Sustainable Energy Reviews, 135, 110116. doi:https://doi.org/10.1016/j.rser.2020.110116

Yang X., Pang J., Teng F., et al. 2021b. The environmental co-benefit and economic impact of china's low-carbon pathways: Evidence from linking bottom-up and top-down models. Renewable and Sustainable Energy Reviews, 136, 110438. doi:https://doi.org/10.1016/j.rser.2020.110438

Yu S., Zheng S., Li X. 2018a. The achievement of the carbon emissions peak in china: The role of energy consumption structure optimization. Energy Economics, 74, 693-707. doi:https://doi.org/10.1016/j.eneco.2018.07.017

Yu S., Zheng S., Li X., et al. 2018b. China can peak its energy-related carbon emissions before 2025: Evidence from industry restructuring. Energy Economics, 73, 91-107. doi:https://doi.org/10.1016/j.eneco.2018.05.012

Yu S., Zheng S., Zhang X., et al. 2018c. Realizing china's goals on energy saving and pollution reduction: Industrial structure multi-objective optimization approach. Energy Policy, 122, 300-312. doi:https://doi.org/10.1016/j.enpol.2018.07.034

Zhang L.P., Zhou P. 2018. A non-compensatory composite indicator approach to assessing low-carbon performance. European Journal of Operational Research, 270, 352-361. doi:https://doi.org/10.1016/j.ejor.2018.02.058

Zhang S., An K., Li J., et al. 2021a. Incorporating health co-benefits into technology pathways to achieve china's 2060 carbon neutrality goal: A modelling study. The Lancet Planetary Health, 5, e808-e817. doi:https://doi.org/10.1016/S2542-5196(21)00252-7

Zhang S., Chen W. 2022. Assessing the energy transition in china towards carbon neutrality with a probabilistic framework. Nature Communications, 13, 87. doi:10.1038/s41467-021-27671-0

Zhang S., Wu Y., Liu X., et al. 2021b. Co-benefits of deep carbon reduction on air quality and health improvement in sichuan province of china. Environmental Research Letters, 16, 095011. doi:10.1088/1748-9326/ac1133

Zhang W.W., Zhao B., Gu Y., et al. 2020. Environmental impact of national and subnational carbon policies in china based on a multi-regional dynamic cge model. Journal of Environmental Management, 270, 110901. doi:10.1016/j.jenvman.2020.110901

Zhong S., Xiong Y., Xiang G. 2021. Environmental regulation benefits for whom? Heterogeneous effects of the intensity of the environmental regulation on employment in china. Journal of Environmental Management, 281, 111877. doi:https://doi.org/10.1016/j.jenvman.2020.111877