Optimal allocation of CO₂ emission quotas at the city level in Bohai Rim Economic Circle based on multi-objective decision approach

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Abstract

As the most developed city circle in northern China, allocating CO₂ emission quotas at the Bohai Rim Economic Circle (BREC) city level is essential for developing specific abatement policies. Thus, with reflecting multi-principles (fairness, efficiency, sustainability, and feasibility), this paper formulates the CO₂ emission quotas allocation among cities in BREC in 2030 based on the multi-objective decision approach. We first propose three allocation schemes based on the principles of fairness, efficiency, and sustainability, which are conducted by entropy method, zero-sum gains data envelopment (ZSG-DEA) model, and CO₂ sequestration share method, respectively.
Then, the CO₂ allocation satisfaction is defined and used to measure the feasibility principle which is integrated as the objective function of the multi-objective decision model together with three allocation schemes to obtain the optimal allocation results. The results show that cities with large energy consumption and less CO₂ sequestration capacity, such as Tianjin, Handan, and Tangshan, experience a decrease in the emission quota shares from 2017 to 2030, indicating that these cities would undertake large emissions reduction obligations. Conversely, there is an increase in the shares of CO₂ emission quotas when it comes to Beijing, Chengde, and Dalian, whose GDP, population, and CO₂ sequestration capacity are relatively large. Sensitivity analysis shows that Beijing, Zibo, and Jinan are more sensitive to minimum satisfaction changes, and the total satisfaction experiences an increase first and declines thereafter. Based on the results above, cities with large pressure to reduce CO₂ emissions should not only promote the economic development, but also improve the capacity of CO₂ sequestration by enhancing environmental protection to realize emission reduction targets.

**Keywords:** CO₂ emission quota allocation; Multi-principles; Cities in Bohai Rim Economic Circle; Multi-objective decision model; Allocation satisfaction.

1. **Introduction**

In order to combat climate change, the Chinese government has undertaken to reduce the national carbon emission intensity by 60%-65% in 2030 compared with 2005 and reach the CO₂ emissions peak before 2030. Besides, in October 2020, China made further commitments to achieve carbon-neutral before 2060. To reduce carbon
emissions intensity, China has committed to implementing the emissions trading scheme (ETS), which is an effective way to reduce CO$_2$ emissions through the market mechanism (Han et al., 2017; Kong et al., 2019; Hu et al., 2020). After implementing seven carbon-trading pilot programs in 2011, China's national ETS was officially launched in December 2017 and started by covering the power sector in this system, while the remaining sectors will be incorporated gradually.

As one of the most essential prerequisites for national ETS, allocating CO$_2$ emission quotas scientifically and reasonably has attracted increasing attention. Studies have focused on CO$_2$ emission quotas allocation at different levels, for example, country level (Benestad, 1994; Pan et al., 2014; Momeni et al., 2018), China's provincial level (Yi et al., 2011; Kong et al., 2019; He and Zhang, 2020; Zhou et al., 2021) and several provinces within specific regions (Han et al., 2016; Chang et al., 2020). With respect to determining the CO$_2$ emission quotas by cities, Li et al. (2018) constructed a comprehensive index using the maximum deviation method to allocate CO$_2$ emission quotas among nine cities in the Pearl River Delta region by 2020. Zhou et al. (2018) evaluated emission performance and allocated CO$_2$ emission quotas to Chinese 71 cities based on the data envelopment analysis (DEA) model. Besides, Liu et al. (2018) determined the CO$_2$ emission quotas among 25 cities in the Yangtze River Delta region by constructing a comprehensive index. The same case study was conducted by Zhang et al. (2020), who simulated the CO$_2$ emission quotas allocation by the ZSG-DEA model. In summary, few studies and methods are focusing on the CO$_2$ emission quotas allocation at the city level.
As the main subject of CO\(_2\) emissions, cities play an essential role in achieving carbon emission reduction targets, providing more accurate information than the provincial level to formulate targeted policies for emissions reduction. Besides, as the most developed area in northern China, BREC consumed a lot of energy, accounting for 25.4% of the national total in 2017 (Chang et al., 2020). The realization of its regional coordinated carbon reduction has strategic importance for realizing China’s national emission reduction target. Chang et al. (2020) proposed a two-stage allocation model to simulate the CO\(_2\) emission quotas allocation for five provinces in BREC in 2030. Han et al. (2016) issued CO\(_2\) emission quotas to three provinces in the Beijing-Tianjin-Hebei region using the composite index approach. However, few studies have been conducted to allocate the CO\(_2\) emission quotas among the cities in BREC. Therefore, it is of great importance to investigate provincial emission quotas allocation among cities.

This paper aims to formulate the CO\(_2\) emission quotas allocation for cities in BREC in 2030.

Furthermore, the principles and methods used can be induced from the existing literature. Generally, fairness and efficiency are two main principles followed by the most current studies. For example, Pan et al. (2014) formulated the fair CO\(_2\) emissions quotas allocation at national levels following equal cumulative emission per capita. As for the efficiency principle, three allocation strategies (spatial, temporal, and spatial-temporal) were adopted by Zhou et al. (2014), who formulated the optimal allocation of CO\(_2\) emission quotas using centralized DEA models. Also, Dong et al. (2018) applied an improved fixed cost allocation model by taking fairness and efficiency principles
both into consideration. The same principles were considered by Kong et al. (2019) and He and Zhang (2020), who combined the entropy method with the DEA model to establish a comprehensive index for the allocation of provincial CO$_2$ emission quotas. Although the principle of fairness and efficiency are most commonly used, the indicators measuring the fairness and efficiency principles failed to reach a unified conclusion. Besides, considering production consistency, feasibility principle was also proposed in the various studies since they believe the CO$_2$ emission quotas should be allocated with strong operational and more readily accepted in practice (Zetterberg et al., 2012; Zhou and Wang, 2016; Li et al., 2018; Zhu et al., 2018; Fang et al., 2018; Fang et al., 2019). In addition, increasing attention has been paid to the principle of sustainability, which caters to the CO$_2$ emission demand of future development (Fang et al., 2018; Fang et al., 2019; Cui et al., 2020; Li et al., 2020; Zhou et al., 2021). For instance, the environmental factors, including the absorptive capacity to sequestrate CO$_2$ and ecosystem service value, are used to reflect the sustainability principle (Fang et al., 2019; Zhou et al., 2021).

To improve the adaptability, multi-criteria scheme has been proposed. For example, Fang et al. (2019) considered the indicators quantifying the principles of fairness, efficiency, feasibility, and sustainability into an improved ZSG-DEA model to determine the CO$_2$ emission quotas at the provincial level. Zhou et al. (2021) carried out a study of China’s CO$_2$ emission quotas allocation program design and efficiency evaluation by 2020, which integrated the principles of fairness, efficiency, and sustainability together to construct a comprehensive index based on entropy method.
Generally, considering multiple principles to explore a compromise scheme is increasingly recognized. Thus, this paper aims to explore the CO₂ emission quotas allocation of cities to achieve the multi-criteria objective.

The commonly used allocation methods to build multi-criteria allocation schemes can be concluded as indicator approach, DEA, nonlinear programming models, game theory, and hybrid or other approaches. The indicator approach, especially the composite index, has been widely used to respond to different principles. For example, Yi et al. (2011) simulated the allocation of national emission target by 2020, integrating carbon reduction responsibility, potential and capacity. Similar studies were conducted by Chang et al. (2016), Han et al. (2016), Tang et al. (2019), and Zhou et al. (2021). Besides, many studies also constructed the comprehensive index combining the DEA model (Qin et al., 2017; Zhou et al., 2017; Liu et al., 2018; Kong et al., 2019; Zhou et al., 2019). However, its subjectivity and arbitrariness have been criticized (Fang et al., 2019). For one thing, most of the indicators selected by previous studies are inconsistent, and the differences in natural resources and the environment have been ignored to a certain extent, except for the studies of Fang et al. (2018) and Zhou et al. (2021). The environmental factor, especially carbon absorption, has a significant impact on the ecosystem’s carbon cycle, which affects the realization of carbon neutrality. Besides, how to determine the weights for different indicators is still controversial.

DEA and ZSG-DEA models have emerged to solve the problem by focusing on the whole system’s efficiency. As a typical optimization method, researchers have proposed various improved DEA models, which provide more innovative ideas and solutions for
CO₂ emission quotas allocation. Similar models can be found in the studies of Zhou et al. (2014), Feng et al. (2015), Wu et al. (2016), An et al. (2017), Momeni et al. (2018), Xie et al. (2019) and Yu et al. (2019). On the basis of the DEA model, THE ZSG-DEA model was developed by reallocating the remaining resources based on the cooperation or competition among DMUs (decision-making units). Wang et al. (2013), Miao et al. (2016), Cucchiella et al. (2018), Cai et al. (2019), Yu et al. (2019), and Fang et al. (2019) used the ZSG-DEA model, selecting different indicators as input and output variables to allocate the CO₂ emission quotas. Besides, Yang et al. (2020) proposed a ZSG-DEA model by improving the iterative approach, which introduces the fairness principle into the efficiency-oriented model to optimize the CO₂ emission reduction scheme for Chinese provinces by 2030. The mechanism of DEA gives priority to the efficiency principle, which may underestimate the effects of other principles. Besides, some studies regarded collaborative carbon abatement as the basis of allocation by game theory (Filar and Gaertner, 1997; Li and Piao, 2013; Zhang et al., 2014). However, the game theory is too complicated to be suitable for the allocation of Chinese cities level.

By contrast, the nonlinear optimization model has emerged as another common method, which explores using the multi-objective decision approach for resource allocation. Table 1 describes the use of nonlinear optimization models with their constraint condition, specifically, considering optimization based on fairness principle (Fang et al., 2018), efficiency principle (Li et al., 2018; Ye et al., 2019), and both fairness and efficiency principles (Yang et al., 2019; Ma et al., 2020). Besides, Zhu et al. (2018) proposed a multi-objective decision model incorporating the principles of fairness,
efficiency, and feasibility to allocate CO₂ emission quotas to six industries in Guangdong. The environmental Gini coefficient is mainly used to realize fairness optimization, while the optimization of efficiency mostly focuses on maximizing economic benefits and minimizing carbon reduction costs. However, the environmental Gini coefficient minimization model cannot consider historical emissions. This study intends to build CO₂ emission quotas allocation solutions with more consensus on fairness and efficiency. In addition, as increasing guidelines are applied to multi-criteria, most nonlinear optimization models for CO₂ emission quotas allocation need to be improved in defining and reflecting allocation principles other than the principles of fairness and efficiency. Thus, it is of great significance to integrate the feasibility and sustainability principles into the multi-objective decision with carbon intensity reduction targets towards 2030.

Considering the prevalence of the multi-objective decisions approach, which can transform the allocation principles into specific mathematical models with constrained boundary condition, this paper proposes a multi-objective decision model, integrating the principles of fairness, efficiency, sustainability, and feasibility, to formulate the allocation of CO₂ emission quotas among cities in BREC by 2030. Specifically, we put forward three allocation schemes based on fairness, efficiency, and sustainability, respectively. The first allocation scheme is based on the principle of fairness. We construct a composite index integrating different fair indicators, including population, GDP, historical CO₂ emissions, and historically accumulated net CO₂ emission, where the historically cumulative net CO₂ emissions are calculated by deducting the CO₂
sequestration of vegetation. Based on this composite index, we use the entropy method to allocate the emission quotas to each city in BREC. As for the second allocation scheme, we simply take the efficiency principle into consideration and use the ZSG-DEA model to obtain each city’s CO₂ emission quotas. The third allocation scheme is based on the sustainability principle and conducted using the proportion of regional carbon sequestration. After receiving three schemes, we further define the CO₂ allocation satisfaction to reflect the feasibility principle. Ultimately, three allocation schemes, as well as the allocation satisfaction (feasibility principle), are integrated into the multi-objective decision model as objective functions. Thus, this multi-objective decision model is proposed to explore the optimal allocation results.

Overall, the contributions of this paper can be described as (1) selecting the cities in BREC as the research object to analyze its CO₂ emission quotas allocation in 2030; (2) integrating the principles of fairness, efficiency, sustainability, and feasibility into a multi-objective decision model; (3) proposing and optimizing the allocation schemes based on the principles of fairness, efficiency, and sustainability to improve the adaptability of schemes; (4) integrating the CO₂ allocation satisfaction for each city to ensure the feasibility of allocation scheme.

**Table 1.** The summary of multi-objective optimization models.

| Research purposes                                           | Optimization objectives                                                                 | Constraint condition                                      |
|--------------------------------------------------------------|----------------------------------------------------------------------------------------|----------------------------------------------------------|
| CO₂ emission quotas allocation for Chinese provinces (Fang et al., 2018) | Minimize the sum of Gini coefficients (accumulated percentage of population, ecological productive land, GDP and fossil energy resources) | Gini coefficient constraint                                |
|                                                              |                                                                                        | CO₂ emission intensity reduction constraint               |
|                                                              |                                                                                        | The restraint of CO₂ emission intensity reduction ratio in different regions: |
| Allocating CO₂ emission quotas to the Pearl River Delta cities (Li et al., 2018) | The minimization of regional abatement costs | Total emissions constraint |
| --- | --- | --- |
| Efficiency principle: economic benefits maximization | The maximization of individual interests | The low and up emission limits |
| CO₂ emission quotas allocation for six industries in Guangdong (Zhu et al., 2018) | Fairness principle: the basic emission right and development performance emission right | Constraints of physical capital stock |
| Feasibility principle: grandfathering | Constraints of human capital | Constraints of CO₂ emission |
| Carbon quotas allocation at the provincial level in China (Yang et al., 2019) | Minimize the carbon Gini coefficient | Industrial output |
| Minimize total CO₂ emission reduction cost | | Pollutant emissions development scale of each industry |
| Allocation of SO₂ emission permits among eight key industries in Jilin (Duan et al., 2019) | Maximize regional industrial output | Industrial restructuring |
| Minimize pollutant emissions | labor resource | environmental protection expenditure |
| CO₂ emission quotas allocation for eight key industries in Guangdong (Ye et al., 2019) | Energy goal: improving emission efficiency | Controlling total emissions |
| Economic goal: reducing abatement cost | Total coal capacity constraints | |
| Regional coal de-capacity allocation in China (Ma et al., 2020) | Maximize the weighted average efficiency based on DEA model | Provincial coal capacity constraints |
| Minimize the Gini coefficients | Labor restraint |

The remainder of this paper is conducted as follows. Section 2 interprets the methods and data sources. Section 3 introduces the CO₂ emission quotas allocation results under single and multi-principles. The sensitivity analysis is provided in Section 4. Section 5 concludes this paper and provides some policy implications.

2. Methodology and data sources

Fig 1. illustrates the schematic of the CO₂ emission quotas allocation adopted by this paper. First, three allocation schemes based on fairness, efficiency, and sustainability
are conducted, respectively. Second, we define the CO\textsubscript{2} allocation satisfaction to measure the feasibility principle of the allocation scheme. Finally, a multi-objective model is established to explore the optimal CO\textsubscript{2} emission quotas allocation solution considering the principles of fairness, efficiency, sustainability, and feasibility together.

In this section, we begin with the method of allocation scheme based on the fairness principle. Then, we introduce the method of allocation schemes based on the principles of efficiency and sustainability, respectively, following which we explain the measurement of feasibility principle. Section 2.5 presents the multi-objective decision model integrating the principles of fairness, efficiency, sustainability, and feasibility. Finally, this section introduces the data sources.

**Fig. 1.** Schematic of CO\textsubscript{2} emission quotas allocation.

### 2.1 Allocation scheme based on the fairness principle
This paper intends to build the compromise allocation scheme considering the fairness principle by constructing a composite index. The indicators selected in this paper follow different perspectives of the fairness principle, as shown in Table 2. It should be noted that the accumulated historical net CO₂ emissions express as the accumulated historical CO₂ emission after deducting CO₂ sequestration from 2005 to 2017, which reflects the attention on environmental factors.

**Table 2.** Four indicators with their criteria and interpretations.

| Indicators                           | Criterion                     | Interpretation                                                                 |
|--------------------------------------|-------------------------------|-------------------------------------------------------------------------------|
| Population (p₁)                      | Egalitarianism                | All people have equal right to pollute and to be protected from pollution (+).|
| Accumulated historical net CO₂ emission (p₂) | Polluter pays/Historical responsibility | Reflect that cities with more historical emissions need to take more abatement burdens, calculated from 2005 to 2017 (-). |
| GDP (p₃)                             | Economic activity/Horizontal fairness | Reflect the allocation should be allowed to maintain their standard of living (+). |
| Historical CO₂ emissions (p₄)        | Sovereignty / Grandfathering  | All cities have equal right to pollute and to be protected from pollution (+). |

To quantify the comprehensive index, we employ the entropy method to determine the weight of each indicator, which has been widely used to build the comprehensive index of CO₂ emission quotas allocation (Feng et al., 2018; Liu et al., 2018; Kong et al., 2019; He and Zhang 2020). The methods are shown as follows:

The following equation can normalize the positive indicator and negative indicator:

\[
x_{ij} = \frac{p_{ij} - \min_{i} p_{ij}}{\max_{i} p_{ij} - \min_{i} p_{ij}} \quad (i = 1, \ldots, 30; j = 1, 2, 3, 4)
\]

(1)

\[
x_{ij} = \frac{\max_{i} p_{ij} - p_{ij}}{\max_{i} p_{ij} - \min_{i} p_{ij}} \quad (i = 1, \ldots, 30; j = 1, 2, 3, 4)
\]

(2)

where \( p_{ij} \) is the value of indicator \( j \) of the city; \( \max_{i} p_{ij} \) and \( \min_{i} p_{ij} \) are the maximum and minimum values of cities, respectively; \( x_{ij} \) is the normalized value of \( p_{ij} \).
Then, we calculate the entropy value of indicator $j$ using equations (3) and (4).

$$y_{ij} = \frac{x_{ij}}{\sum_{i=1}^{44} x_{ij}} \quad (i = 1, \ldots, 44; j = 1, 2, 3, 4)$$  \hspace{1cm} (3)$$

$$m_j = -(\ln 44)^{-1} \sum_{i=1}^{44} [(y_{ij} \times \ln (y_{ij})] \quad (i = 1, \ldots, 44; j = 1, 2, 3, 4)$$  \hspace{1cm} (4)$$

where $y_{ij}$ is the share of indicator $j$ of city $i$ in the sum of indicator $j$ of all cities; $m_j$ is the entropy of indicator $j$. And if $y_{ij} = 0$, then $\ln (y_{ij}) = 0$.

Next, we calculate the weight of each indicator and construct a comprehensive index.

The weight of indicator $j$ ($r_j$) can be calculated using equation (5).

$$r_j = \frac{1 - m_j}{\sum_j (1 - m_j)} \quad (j = 1, 2, 3, 4)$$  \hspace{1cm} (5)$$

The comprehensive index ($h_i$) can be built by equation (6).

$$h_i = r_1y_{i1} + r_2y_{i2} + r_3y_{i3} + r_4y_{i4} \quad (i = 1, \ldots, 44)$$  \hspace{1cm} (6)$$

Finally, we calculate the weight for city $i$ by equation (7).

$$w_i = \frac{h_i}{\sum_{i=1}^{44} h_i} \quad (i = 1, \ldots, 44)$$  \hspace{1cm} (7)$$

After the comprehensive index of each city was obtained, we calculate the CO$_2$ emission quotas that each city should be allocated, represented as the equation (8).

$$C_{fi} = w_i \times C_{2030} \quad (i = 1, \ldots, 44)$$  \hspace{1cm} (8)$$

where $C_{fi}$ is the CO$_2$ emission quotas of the city $i$ allocated based on the fairness principle, $C_{2030}$ is the total CO$_2$ emissions in BREC in 2030.

The optimization of fairness requires the allocation results to be as close as possible to $C_{fi}$ with the constraints. We develop the fairness degree function of CO$_2$ emission allocation as $F_1 = \sum_{i=1}^{n} (C_i - C_{fi})^2$. If $F_1 = 0$, the allocation results are consistent with the fairness scheme. The objective function of fairness is expressed as:

$$\min F_1 = \sum_{i=1}^{n} (C_i - C_{fi})^2$$  \hspace{1cm} (9)$$
2.2 The allocation scheme based on the efficiency principle

This paper applies the ZSG-DEA model to search for optimal CO$_2$ emissions with all cities on the DEA efficiency frontier. As the total CO$_2$ emissions in 2030 remain constant, the ZSG-DEA model can obtain the optimal allocation results by reallocating the redundant CO$_2$ emission among all cities. And it has been widely used to allocate CO$_2$ emission quotas, for example, taking CO$_2$ emissions as undesirable output, Wang et al.(2013) and Miao et al. (2016) adopted output-oriented ZSG-DEA model to formulate the allocation of CO$_2$ emission quotas. Conversely, the input-oriented ZSG-DEA models are also developed considering CO$_2$ emission as an input variable to formulate the allocation of CO$_2$ emission quotas (Cai et al.,2019; Fang et al.,2019; Yu et al.,2019). We adopt an input-oriented ZSG-DEA model to obtain optimal CO$_2$ emissions for each city. We consider energy consumption, labor, and GDP as three output variables and CO$_2$ emissions as an input variable, as shown in Table 3. The initial CO$_2$ emissions for each city in 2030 are obtained by the proportion of CO$_2$ emissions in 2017, where is called grandfathering.

Table 3. Input and output variables of the ZSG-DEA model.

| Variable   | Explanation                                                                 |
|------------|------------------------------------------------------------------------------|
| Inputs     |                                                                              |
| Labor      | The number of staffs in each city                                             |
| Energy     | The energy consumption in each city, with being computed into coal equivalent |
| GDP        | GDP of each city, with all the values being converted into 2005 constant price|
| Output     |                                                                              |
| CO$_2$ emissions | CO$_2$ emissions in each city in 2030, calculated by grandfathering |

The input-oriented ZSG-DEA model is expressed as:
\[
\begin{align*}
\min & \varphi_0 \\
\sum_{i=1}^{44} \lambda_i C_{gi} \left[ 1 + \frac{C_0 (1 - \varphi_0)}{\sum_{i \neq 0} C_{gi}} \right] & \leq \varphi_0 C_0 \\
\sum_{i=1}^{44} \lambda_i E_i & \geq E_0 \\
\sum_{i=1}^{44} \lambda_i L_i & \geq L_0 \\
\sum_{i=1}^{44} \lambda_i Y_i & \geq Y_0 \\
\sum_{i=1}^{44} \lambda_i &= 1 \\
\lambda_i & \geq 0 \ (i = 1, \ldots, 44)
\end{align*}
\]

(10)

where \( \varphi_0 \) is the efficiency value of the DMU being evaluated; \( C_0, Y_0, L_0, E_0, A_0 \) are the values of the corresponding variables of the DMU being evaluated; \( E_i, L_i, Y_i \) are the energy consumption, labor and GDP of the \( ith \) DMU in 2030, respectively. \( \lambda_i \) is the share of the \( ith \) DMU; \( C_{gi} \) is the actual CO\(_2\) emission of the \( ith \) DMU in 2030.

For \( DMU_k (k = 1, \ldots, 44) \) with an inefficient DEA efficiency of \( \varphi_k \) and an initial emission quota of \( C_k \) must reduce its CO\(_2\) emissions by \( C_k (1 - \varphi_k) \). The remaining DMUs must increase their CO\(_2\) emissions by \( C_i \times \frac{C_k (1 - \varphi_k)}{\sum_{i \neq k} C_i} \) (Fang et al., 2019).

Finally, we can obtain the optimal CO\(_2\) emission of each city, expressed by \( C_{ei} \).

After obtaining each city’s optimal CO\(_2\) emissions (\( C_{ei} \)), the efficiency objective of CO\(_2\) emission allocation is built as \( F_2 = \sum_{i=1}^{n} (C_i - C_{ei})^2 \). If \( F_2 = 0 \), the allocation results follow the optimal efficiency scheme. The optimal solution is built to minimize \( \sum_{i=1}^{n} (C_i - C_{ei})^2 \), which can be described by the following equation:

\[
\min F_2 = \sum_{i=1}^{n} (C_i - C_{ei})^2
\]

(11)

2.3 The allocation scheme based on sustainability principle

When allocating CO\(_2\) emission quotas, increasing attention has been paid to the principle of sustainability. Fang et al. (2018) used urbanization rate, the proportion of the tertiary industry, and forest coverage rate to represent the sustainability principle of
social, economic, and environmental dimensions, respectively. A similar approach was used by Li et al. (2020), who applied forest coverage rate, population growth rate, and GDP growth rate as sustainability indicators. Zhou et al. (2021) adopted ecosystem service value as the indicator to reflect the sustainability principle.

This paper uses carbon sequestration capacity as the sustainability principle of CO2 emission quotas allocation. We can calculate the CO2 emission quotas based on the CO2 sequestration capacity of each city, as shown in the following equation.

\[ C_{si} = \frac{S_i}{\sum_{i=1}^{n} S_i} \times C_{2030} \]  

where \( C_{si} \) is CO2 emission quotas of city \( i \), allocated based on the sustainability principle. \( S_i \) is CO2 sequestration of city \( i \) in 2017.

Similarly, the sustainability objective of CO2 emission allocation can be built as \( F_2 = \Sigma_{i=1}^{n} (C_i - C_{si})^2 \). If \( F_2 = 0 \), the allocation results are equal to \( C_{si} \) for each city. The objective function is shown as:

\[ \min F_3 = \Sigma_{i=1}^{n} (C_i - C_{si})^2 \]  

2.4 The feasibility of CO2 emission quotas allocation

The feasibility principle means that the allocation of CO2 emission quotas should maintain production consistency, which is easy to be accepted and implemented (Zhu et al., 2018). This paper uses the “CO2 allocation satisfaction” to estimate the feasibility of CO2 emission quotas allocation. For each city, if the allocated CO2 emission quotas are larger than the CO2 emission expectation, the degree of satisfaction is 1; by contraries, if the minimum CO2 emission expectation is not met, the satisfaction degree is 0. The CO2 allocation satisfaction function degree is described as follows:
\[ U_i = \begin{cases} \frac{C_i - C_i^{\min}}{C_i^{\max} - C_i^{\min}} & C_i^{\max} < C_i < C_i^{\min} \\ 1 & C_i \geq C_i^{\max} \\ 0 & C_i \leq C_i^{\min} \end{cases} \] (14)

where \( C_i^{\max} \) and \( C_i^{\min} \) are the upper and lower limits of CO\(_2\) emission feasibility interval for city \( i \), respectively. Although grandfathering has less impact on production and fewer political barriers (Zetterberg et al., 2012; Zhu et al., 2018), it has been criticized for its limitations on punishing efficient carbon firms while rewarding carbon-intensive firms (Zhou and Wang, 2016). Feng et al. (2018) proposed a weighted voting model to quantify the voting rights of each city to select the CO\(_2\) allocation schemes based on population, GDP, and historical emissions, which are intuitive and clear.

Besides, Dong et al. (2018) analyzed the allocation schemes based on historical emissions, population, and per capita GDP (pays ability egalitarian), then optimized the CO\(_2\) emission quotas based on a modified fixed cost allocation model. Inspired by the work of Dong et al. (2018) and Feng et al. (2018), this paper analyzes the three scenarios (population, GDP, and historical emissions) to determine the feasibility of CO\(_2\) emissions quotas allocation as well as allocation satisfaction interval, presented as:

\[ C_i^{\max} = \max (C_{popi}, C_{gdp_i}, C_{gi}) \] (15)

\[ C_i^{\min} = \min (C_{popi}, C_{gdp_i}, C_{gi}) \] (16)

where \( C_{popi}, C_{gdp_i} \) and \( C_{gi} \) are allocation results based on population, GDP, and historical emissions. The year 2017 is considered as a reference.

As for the feasibility of CO\(_2\) emission quotas allocation, there is no doubt that the higher CO\(_2\) allocation satisfaction, the easier it to accept and implement. And the most acceptable scheme requires maximizing the satisfaction of each city. However, it is
impossible for all of the cities to reach their maximum CO$_2$ allocation satisfaction. We aim at maximizing the sum of minimum CO$_2$ allocation satisfaction for all cities, described as:

$$max\ F_4 = \sum_{i=1}^{n} U_i$$  \hspace{1cm} (17)

2.5 The multi-objective CO$_2$ emission quotas allocation

As stated in Section 2.1-2.4, the multi-objective CO$_2$ emission quotas allocation model can be described as follows:

$$\begin{cases} 
\min F_1 = \sum_{i=1}^{n} (C_i - C_{f_i})^2 \\
\min F_2 = \sum_{i=1}^{n} (C_i - C_{e_i})^2 \\
\min F_3 = \sum_{i=1}^{n} (C_i - C_{s_i})^2 \\
max F_4 = \sum_{i=1}^{n} U_i \\
\sum_{i=1}^{n} C_i = C_{2030} 
\end{cases} \hspace{1cm} (18)$$

The proposed model (18) is a multi-objective model. We can convert multiple goals into a single-objective model to seek the optimal value. Although equation (17) maximizes the total minimum CO$_2$ allocation satisfaction, it may be based on sacrificing the satisfaction of some cities. Considering the feasibility of allocation for each city, equation (17) is converted by the following constraint:

$$1 \geq U_i \geq a$$  \hspace{1cm} (19)

where $\alpha$ is the minimum satisfaction acceptable to each city.

The original model (18) can be converted into the following form.

$$\begin{cases} 
\min F = b_1 * F_1 + b_2 * F_2 + b_3 * F_3 \\
\sum_{i=1}^{n} C_i = C_{2030} \\
1 \geq U_i \geq a \\
b_1 + b_2 + b_3 = 1 \\
b_1 > 0, b_2 > 0, b_3 > 0 
\end{cases} \hspace{1cm} (20)$$
where \( b_1 \), \( b_2 \) and \( b_3 \) are the weights of fairness, efficiency, and sustainability principles.

### 2.6 Data sources

This paper allocates the CO\(_2\) emission quotas for 44 cities in BREC. GDP is collected from China Statistical Yearbook (China National Bureau of Statistics, 2006-2018a), Hebei Statistical Yearbook (Hebei Provincial Bureau of Statistics, 2006-2018), Shandong Statistical Yearbook (Shandong Provincial Bureau of Statistics, 2006-2018), and Liaoning Statistical Yearbook (Liaoning Provincial Bureau of Statistics, 2006-2018). The population and labor are from the China City Statistical Yearbook (China National Bureau of Statistics, 2006-2018b).

Original data of provincial energy consumption in this paper is collected from the China Energy Statistical Yearbook (China National Bureau of Statistics, 2006-2018c). The historical CO\(_2\) emissions and CO\(_2\) sequestration capacity are collected from the work of Chen et al. (2020). More information about the calculation of CO\(_2\) emissions at the city level can be found in the study of Chen et al. (2020). To ensure that the sum of CO\(_2\) emissions in all cities are in line with the provincial total CO\(_2\) emissions, this paper makes correction about the CO\(_2\) emissions in each city by dividing a correction factor, which is calculated as the ratio of total CO\(_2\) emissions in all cities to the provincial CO\(_2\) emissions. The provincial CO\(_2\) emissions are calculated from fossil energy consumption. Based on the city's CO\(_2\) emissions, we calculate the standard coal consumption of each city by dividing the CO\(_2\) emissions by the emission coefficient.

Since we do the emissions allocation in 2030, the total CO\(_2\) emissions in BREC in 2030...
are required. The China’s emission reduction target is to reduce the carbon intensity by 60%-65% in 2030, compared with 2005. We set the same reduction target for BERC and assume that the emission target of 60% in 2030 will be realized. The total CO\textsubscript{2} emissions in BREC in 2030 (\(C_{2030}\)) can be calculated as \(C_{2030} = (1 - 60\%) \times CI_{2005} GDP_{2030}\), where \(CI_{2005}\) is the CO\textsubscript{2} intensity in 2005 and \(GDP_{2030}\) is the GDP in 2030.

As illustrated in the methods, the population, labor, GDP, and energy consumption in this paper should be predicted to 2030. We first calculate the total population of each city in 2030 based on the annual average growth rate of population for each city from 2005 to 2017. According to the provincial development planning, the populations in Beijing, Tianjin, Hebei, Shandong, and Liaoning in 2030 are 2300, 2150, 7910, 4500, and 10667 ten thousand, respectively. To ensure that the sum of the population of cities in each province is consistent with the provincial predictions from provincial development planning, we correct the estimated population of each city in 2030 using the reference data of the total provincial population. The initial estimate data is divided by a correction factor, defined as the ratio of the sum of population in all cities to the provincial predictions. Based on the population forecast, we multiply the population by the share of the labor force in the population of each city to calculate the labor, which is calculated by the proportion of employees to the population in 2017.

To estimate the GDP of each city, we first forecast provincial GDP using the annual average growth rate of GDP for each province from 2005 to 2017. According to Energy Outlook 2050 (2019), China’s GDP growth rate will be approximately 6.7% before
2020 and approximately 5% between 2021 and 2035. Based on the related growth rate of China’s GDP, we predict China’s GDP until 2030. Then using China’s GDP, we correct the provincial GDP by a correction factor, which is calculated by the ratio of the sum of GDP in all provinces to the national predictions. All the values are converted into 2005 constant price. After the provincial GDP is obtained, we use the same prediction method with population to estimate the GDP of each city in 2030. Following the same method, we estimate the energy consumption of each city in 2030. We assume that China’s total energy consumption is 6 billion tons of standard coal for reference. The reference data is from the energy production and consumption revolution strategy (2016-2030).

2.7 Scenario setting

We attempt to analyze the CO₂ emission quotas allocation results under various decision preferences of decision-makers. Four scenarios include equal weights, preferring fairness, preferring efficiency, preferring sustainability. b₁, b₂ and b₃ in Table 4 are the weights of the allocation principles of fairness, efficiency, and sustainability, respectively.

**Table 4.** The weights in four cases.

| Weight                        | b₁    | b₂   | b₃   |
|-------------------------------|-------|------|------|
| Case 1: equal weights         | 1/3   | 1/3  | 1/3  |
| Case 2: preferring fairness   | 0.6   | 0.2  | 0.2  |
| Case 3: preferring efficiency | 0.2   | 0.6  | 0.2  |
| Case 4: preferring sustainability | 0.2  | 0.2  | 0.6  |

3. Results
3.1 Allocation results based on fairness principle

According to the interpretation of fair CO2 emission quotas allocation in previous literature, this paper uses four indicators selected from different perspectives of fairness principle to obtain the allocation scheme based on fairness, including population, GDP, historical cumulative net CO2 emissions, and historical carbon emission. We calculated the weights of these four indicators using the entropy method. As shown in Table 5, the weight of GDP is the largest, followed by population and historical CO2 emission, while historical cumulative net CO2 emissions appears the minimal importance. The environmental Gini coefficient based on population is 0.115 less than 0.2, which means that the allocation results are absolutely fair.

**Table 5.** The weights of indicators and fairness test of the CO2 emission allocation scheme

| Principle          | Fairness | Fairness test |
|--------------------|----------|---------------|
| Indicator          | Population | GDP | Historical cumulative net carbon emissions | Historical carbon emissions | G_{pop} |
| Weight             | 30.19%    | 44.92% | 5.08% | 19.81% | 0.115 |

G_{pop} is the environmental Gini coefficient based on population, which is calculated by trapezoidal area method referring to the formula of Kong et al (2019).

Fig. 2 displays the results of CO2 emission quotas allocation based on fairness in 2030. The regions with higher GDP, population, and historical CO2 emission, tend to obtain more CO2 emission quotas, even though their historical responsibility may be larger, as the weight of historical cumulative net carbon emissions is the smallest. For example, Beijing, Tianjin, Qingdao, and Shijiazhuang, are the four cities having the highest emission quotas allocation, accounting for more than 25.10% of the total. The share of CO2 emission quotas in fourteen cities are less than 1.0 % in 2030. Among them, Laiwu and Fuxin enjoy the lowest CO2 emission quotas allocation proportions of 0.31% and...
0.38%, respectively.

Fig. 2. The CO₂ emissions quotas allocation based on fairness in 2030.

3.2 Allocation results based on efficiency principle

This paper uses the ZSG-DEA model to attain each city’s CO₂ emission quotas based on the efficiency principle. Fig. 3 depicts the DEA efficiency changes for each allocation. The allocation efficiency using the ZSG-DEA model in twenty-one cities is less than the average initial allocation efficiency of 0.89. Only five out of 44 cities have reached the DEA frontier. Tangshan experiences the lowest initial allocation efficiency of 0.8. After the first reallocation, tremendous changes are found, in which the DEA efficiency of all cities is above 0.97 and the average efficiency increases to 0.99, even though no additional cities achieve optimal DEA efficiency. With the completion of the second reallocation, twelve cities have the efficiency of 1, while the remaining cities are close to DEA frontier. Ultimately, all the cities obtain the optimal efficiency of 1.

Fig. 4 describes the initial CO₂ emission and reallocation results for each city. The initial CO₂ emission is completely dependent on each city’s historical emissions. We can find that CO₂ emission quotas increase in fifteen cities (e.g., Tianjin, Beijing, Dalian). Conversely, a decrease in the CO₂ emission quotas is witnessed in nineteen
cities, including Tangshan, Shijiazhuang, Cangzhou, and Langfang. Besides, the CO₂ emission quotas in Jining, Taian, Rizhao, Linyi, Liaocheng, Zaozhuang, Shenyang, and Xingtai remain stable. The reallocation results indicate that Tianjin reports the largest CO₂ emission quotas with the value of 302 million tons (Mt), followed by Beijing (183 Mt), Tangshan (155 Mt), Shijiazhuang (144 Mt), and Weifang (138 Mt). While Laiwu, Dandong, Benxi, Fuxin, and Rizhao experience the smallest, with the value of 13 Mt, 34 Mt, 36 Mt, 37 Mt, and 38 Mt, respectively.

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**Fig. 3.** The DEA efficiency of initial allocation and reallocation.
3.3 Allocation results based on sustainability principle

Fig. 5 compares each city’s CO\textsubscript{2} emission with their CO\textsubscript{2} sequestration and measures the environment pressure defined as CO\textsubscript{2} emission minus CO\textsubscript{2} sequestration in 2017. It can be found that the majority of cities have produced excessive CO\textsubscript{2} emissions, and the CO\textsubscript{2} sequestration of BREC is 776.45 Mt in 2017, which is far lower than the CO\textsubscript{2} emissions (1485 Mt) in the same period. Thus, it is difficult to achieve carbon neutralization only through the absorption effect of the environment on CO\textsubscript{2}. Meanwhile, negative environment pressure can be found in Chengde, Zhangjiakou, Dandong, Chaoyang, Fushun, Benxi, and Dalian, whose CO\textsubscript{2} sequestration has already exceeded their CO\textsubscript{2} emission by 41Mt, 31 Mt, 21 Mt, 10 Mt, 7 Mt, 6 Mt, 5 Mt, respectively. Fuxin, Tiebing, and Huludao have a slight surplus of CO\textsubscript{2} sequestration, which are approaching to the breakeven point (less than 0.30 Mt). By contrast, Laiwu, Rizhao, Jinzhou, Yingkou, Qinhuangdao, Weihai, and Liaoyang are under relatively low environmental pressure (less than 10.0 Mt). The remaining cities, including Beijing, Tianjin, and Shijiazhuang, are facing higher environmental pressure with a massive
shortage of CO₂ sequestration (more than 10.0 Mt).

Fig. 5. The comparison of CO₂ emission of each city with CO₂ sequestration and their environment pressure.

The CO₂ emissions quotas allocation based on sustainability in 2030 are shown in Fig. 6. The cities with higher carbon sequestration capacity will be allocated with larger shares of emission quotas. Chengde, Zhajiakou and Dalian, account for the largest proportion with 7.1 %, 7.0%, and 5.4%, respectively. The emissions quotas in five cities, including Laiwu, Panjin, Liaoyang, Langfang, and Zaozhuang, stay at the lowest level and account for less than 1% of the total in 2030.
3.4 The feasibility interval of CO$_2$ emission quotas

Different from the principles of fairness, efficiency, and sustainability, this paper defines the CO$_2$ allocation satisfaction to measure the feasibility principle. Specifically, inspired by Feng et al. (2018), who provided three allocation schemes, including population-based, GDP-based and historical emissions-based, for each region to select its incline one, we analyze the above three scenarios to determine the allocation interval. Although there is no allocation scheme that can satisfy the favor of all cities, it is deemed as better to obtain more emission quotas (Feng et al., 2018; Xie et al., 2019). Therefore, each city tends to choose the option that is most beneficial to them. Table 6 presents the allocation selected by each city, and the CO$_2$ allocation satisfaction interval is also given. The allocation based on GDP is dominant in fifteen cities, such as Beijing, Tianjin, and Xingtai. There are sixteen cities, who choose the allocation scheme based on historical CO$_2$ emission, classified into the second echelon, while the population-based allocation scheme contributes the most to the remaining thirteen cities. As for the satisfaction interval span, the gap between the maximum and minimum CO$_2$ emissions of Beijing is the largest (287 Mt), followed by Tianjin (220 Mt), Tangshan (144 Mt), Baoding (142 Mt), and Handan (133 Mt). The differences between upper and lower bounds of CO$_2$ allocation satisfaction interval in Laiwu, Rizhao, Benxi, Anshan, Dongying, Fushun, Yingkou, Zhangjiakou, and Zaozhuang are less than 20 Mt. Among them, those of Laiwu and Rizhao are 9 and 10 Mt, respectively.

Table 6. The allocation schemes selected by each city (Unit: Mt).

| Cities     | Selected schemes | Maximum | Minimum | Interval span |
|------------|------------------|---------|---------|---------------|
|            |                  |         |         |               |
| City          | Indicator       | Emissions | GDP  | Historical Emission |
|--------------|----------------|-----------|------|---------------------|
| Beijing      | GDP            | 449       | 162  | 287                 |
| Tianjin      | GDP            | 385       | 165  | 220                 |
| Shijiazhuang | Historical emission | 161   | 132  | 29                  |
| Tangshan     | Historical emission | 173   | 28   | 144                 |
| Qinhuangdao  | Historical emission | 53    | 28   | 25                  |
| Handan       | Population     | 166       | 33   | 133                 |
| Xingtai      | GDP            | 148       | 93   | 55                  |
| Baoding      | Population     | 190       | 48   | 142                 |
| Zhangjiakou  | GDP            | 78        | 60   | 17                  |
| Chengde      | GDP            | 89        | 38   | 51                  |
| Cangzhou     | Historical emission | 135   | 33   | 102                 |
| Langfang     | Historical emission | 108   | 46   | 62                  |
| Hengshui     | GDP            | 85        | 57   | 28                  |
| Shenyang     | Historical emission | 154   | 116  | 38                  |
| Dalian       | GDP            | 180       | 94   | 86                  |
| Anshan       | GDP            | 67        | 54   | 13                  |
| Fushun       | Historical emission | 43    | 26   | 17                  |
| Benxi        | Historical emission | 34    | 23   | 10                  |
| Dandong      | Population     | 37        | 23   | 15                  |
| Jinzhou      | Historical emission | 48    | 26   | 22                  |
| Yingkou      | Historical emission | 49    | 32   | 17                  |
| Fuxin        | Historical emission | 35    | 8    | 27                  |
| Liaoyang     | Historical emission | 47    | 24   | 23                  |
| Panjin       | Historical emission | 51    | 21   | 30                  |
| Tieling      | Historical emission | 60    | 17   | 42                  |
| Chaoyang     | Population     | 53        | 15   | 38                  |
| Huludao      | Historical emission | 45    | 19   | 26                  |
| Jinan        | GDP            | 151       | 101  | 50                  |
| Qingdao      | GDP            | 221       | 127  | 94                  |
| Zibo         | GDP            | 117       | 68   | 48                  |
| Zaozhuang    | Population     | 66        | 48   | 18                  |
| Dongying     | GDP            | 100       | 31   | 69                  |
| Yantai       | GDP            | 173       | 103  | 70                  |
| Weifang      | Population     | 148       | 123  | 25                  |
| Jining       | Population     | 139       | 101  | 38                  |
| Taian        | Population     | 90        | 65   | 25                  |
| Weihai       | GDP            | 96        | 40   | 56                  |
| Rizhao       | Population     | 48        | 38   | 10                  |
| Laiwu        | GDP            | 21        | 11   | 9                   |
| Linyi        | Population     | 182       | 104  | 77                  |
| Dezhou       | Population     | 94        | 70   | 23                  |
| Liaocheng    | Population     | 100       | 60   | 40                  |
| Binzhou      | Historical emission | 81    | 55   | 26                  |
Heze  Population  160  44  116
Total - 5108  2614 -

3.5 The comparison of allocation results based on single principle

Fig. 6 delineates the contributions of the principles of fairness, efficiency, and sustainability to each city. Generally, there are both conflicts and agreements between the principles of fairness, efficiency, and sustainability. The fairness principle is gained prominence in eleven cities, including Beijing, Xingtai, Tianjin, Jinan, Zibo, Qingdao, and Shijiazhuang, whose proportion of allocation results based on the fairness principle is the largest compared with the other two principles. In the case of Beijing, for example, results indicate that the proportion of fairness has reached 52.2%. Eleven cities (e.g., Langfang, Tangshan, Tianjin, Shenyang) have the advantage of reflecting the efficiency principle, many of which are located in Hebei and Liaoning. The sustainability principle is dominated in thirteen cities (e.g., Dandong, Chengde, Zhangjiakou, Fushun, Benxi), especially in Chengde, the allocation proportion based on sustainability is 71.0%. Additionally, the agreements exist in the remaining ten cities, in which the principles contribute similarly. For example, the proportion of fairness, efficiency, and sustainability principles in Linyi is 35.9%, 32.0%, 32.1%.
We further calculate the satisfaction of single principle-based allocation scheme using Eq (14)-(16). As shown in Fig. 7, the average of CO$_2$ allocation satisfaction based on the efficiency principle is the largest (0.53), followed by the principles of sustainability (0.44) and fairness (0.40). Thus, the allocation scheme based on the efficiency principle is the most feasible one. However, there are thirteen cities with low satisfaction (less than 0.2), among which the CO$_2$ allocation satisfaction in six cities is equal to 0. Only eight cities' satisfaction is lower than 0.2 in the fairness allocation scheme. Furthermore, this situation in the allocation scheme based on sustainability appears even worse than the principles of fairness and efficiency, which emerges as eighteen cities have low CO$_2$ allocation satisfaction, with which less than 0.1. The standard variance of CO$_2$
allocation satisfaction is the smallest in the fairness allocation scheme (0.12) among the three allocation schemes.

![Graph showing CO₂ allocation satisfaction by cities based on each principle]

**Fig. 7.** The satisfaction of CO₂ allocation of cities by principle.

### 3.6 Multi-objective CO₂ quotas allocation results

In order to improve the allocation results based on single principle, this paper proposes a multi-objective CO₂ emission quotas allocation model. The results of different cases are reported in Table 7. The minimum CO₂ allocation satisfaction α = 0.3 is set as the baseline scenario. The CO₂ emission quotas in seventeen cities, such as Shijiazhuang, Chaoyang, Huludao, Jinan, and Liaocheng, are approximately equal in different cases. We also find that the satisfaction of those cities is close to the upper and lower limits of
constraints, which means the CO₂ allocation satisfaction constraint decides their allocation results. Different characteristics are shown in the remaining cities. For example, Dalian obtains the largest CO₂ emission quotas under Case 4 (preferring sustainability) with 180 Mt. In comparison, the lowest one is case 3 (preferring efficiency) with 143 Mt. Beijing is allocated with the highest CO₂ emission quotas in Case 2 (preferring fairness) with 260 Mt. Emission quotas obtained by Beijing are the same in remaining cases. For Tianjin, the allocation results in Cases 1 and 4 are equal to 231 Mt, AND the largest quota is from Case 2 (255 Mt), followed by Case 3 (251Mt).

In Case 1 (equal weights), Beijing, Tianjin, Dalian, Shijiazhuang, Yantai, Weifang, and Linyi enjoy the largest CO₂ emission quotas, 1180 Mt in total, and accounting for 31%. Compared with the initial CO₂ emissions obtained by grandfathering, the final results under the case of equal weights indicate that fifteen out of the 44 cities are found to cut down their CO₂ emission quotas, including Langfang, Tangshan, and Cangzhou, while ten cities (Qinhuangdao, Anshan, Fushun, and Benxi) remain stable and the remaining nineteen cities such as Beijing, Qingdao, and Yantai, experience the increase of emission quotas.

Table 7. The CO₂ emission quotas allocation results in 2030 under various decision preferences (Unit: Mt).

| Cities          | Initial CO₂ emissions (grandfathering) | Case 1: equal weights | Case 2: preferring fairness | Case 3: preferring efficiency | Case 4: preferring sustainability |
|-----------------|----------------------------------------|-----------------------|-----------------------------|-------------------------------|----------------------------------|
| Beijing         | 162                                    | 248                   | 260                         | 248                           | 248                              |
| Tianjin         | 267                                    | 231                   | 255                         | 251                           | 231                              |
| Shijiazhuang    | 161                                    | 140                   | 140                         | 140                           | 140                              |
| Tangshan        | 173                                    | 115                   | 105                         | 126                           | 109                              |
| Qinhuangdao     | 53                                     | 52                    | 46                          | 47                            | 53                               |
| Handan          | 131                                    | 96                    | 98                          | 103                           | 84                               |
| Xingtai         | 93                                     | 109                   | 111                         | 109                           | 109                              |
Table 7 shows that Case 2 is beneficial to Beijing, Tianjin, Dongying, Weifang, Linyi, and Heze, in which they obtain the largest emission quotas among the four cases. Conversely, it is not beneficial to Tangshan, Qinhuangdao, Jinzhou, Yingkou. Some cities such as Tangshan, Handan, Cangzhou, Shenyang, Liaoyang, and Panjin prefer
Case 3, while Qinhuangdao, Baoding, Dalian, and Yantai incline to choose Case 4.

Fig. 8 displays the sum of CO$_2$ allocation satisfaction of 44 cities with different decision cases. The greatest CO$_2$ allocation satisfaction is Case 4 with 25.58. The following are Cases 1 and 3, which are 25.12 and 24.07, respectively, while the lowest one is Case 2 with 23.72. Therefore, the allocation preferring sustainability is the most feasible among the four cases.

![Fig. 8](image)

**Fig. 8** The sum of CO$_2$ allocation satisfaction with various decision preferences.

Compared with the single principle-based allocation scheme, fewer differences exist in the results of multi-object models with various cases, which means that allocation results of multi-objective models under different cases present a smaller variance. For example, the CO$_2$ emission quotas of Heze are equal to 37 Mt in multi-objective models under four cases. In contrast, the largest CO$_2$ emission quotas in the single principle-based allocation scheme are 6.26 times the size of the smallest. Allocation schemes based on fairness and sustainability principles have low CO$_2$ allocation satisfaction, conflicting with the feasibility principle. The scheme based on efficiency cannot achieve a fair allocation. Serious conflicts exist in the principles of fairness, efficiency
and, sustainability in some cities (e.g., Beijing, Langfang, Tieling). Therefore, the scheme based on a single principle inevitably distorts the allocation results. However, the multi-objective model can effectively integrate the principles of fairness, efficiency, sustainability, and feasibility, the results can eliminate the conflicts between multiple principles and become more reasonable with less discrepant across various cases.

4. Sensitivity analysis

The minimum CO$_2$ allocation satisfaction ($a$) measures the feasibility of the allocation scheme, which is exogenously set by estimation and the authority. The value of $a$ decides the CO$_2$ emissions constraint for each city and play an essential role in the allocation. Therefore, it is necessary to consider the robustness tests.

We set $a=0.3$ as the baseline scenario and only change the value of $a$ to test the sensitivity of carbon emission quotas allocation. Expressly, we set $a$ at low and high levels: 0 and 0.48, and search the optimal solutions, respectively. When the minimum CO$_2$ allocation satisfaction ($a$) is higher than 0.48, the model has no feasible solution.

The sum of minimum CO$_2$ emissions of all cities would exceed the targeted total CO$_2$ emission. We take the case of equal weight as an example. The allocation results of choosing different values of $a$ are shown in Table 8.

| Cities       | $a=0$ | $a=0.1$ | $a=0.2$ | $a=0.3$ | $a=0.4$ | $a=0.45$ | $a=0.48$ |
|--------------|-------|---------|---------|---------|---------|----------|----------|
| Beijing      | 217   | 216     | 219     | 248     | 277     | 291      | 300      |
| Tianjin      | 229   | 228     | 227     | 231     | 253     | 264      | 271      |
| Shijiazhuang | 132   | 135     | 138     | 140     | 143     | 145      | 146      |
| Tangshan     | 120   | 119     | 118     | 115     | 105     | 94       | 98       |
| Qinhuangdao  | 53    | 53      | 53      | 52      | 42      | 40       | 40       |
| Handan       | 101   | 101     | 100     | 96      | 86      | 93       | 97       |
| Xingtai      | 100   | 100     | 104     | 109     | 115     | 118      | 119      |
When $\alpha$ is up from 0 to 0.48, cities with low CO$_2$ allocation satisfaction increase their CO$_2$ emission quotas, typical examples including Beijing, Tianjin, Shijiazhuang, Jinan, Zibo, Zaozhuang, Jining, and Taian. Conversely, eighteen cities (e.g., Tangshan, Qinhuangdao, Chaoyang) first keep their CO$_2$ emission quotas constant with the
increase of value $a$. Then their emission quotas decrease when $a$ exceeds a specific value. Besides, the CO$_2$ emission quotas in some cities such as Handan, Baoding, Linyi, Heze, decrease first and increase thereafter. The emission quotas in Beijing increase by 38.2%, followed by Zibo and Jinan, with 22.2% and 21.8%, respectively. Fuxin, Chaoyang, and Tieling show the largest reduction proportion of their emission quotas (more than 30%). Some cities are less sensitive to the change of value $a$. For instance, Shenyang only increases by 0.9%, and Weifang decreases by 2.0%.

Fig. 9 reflects the tendency of the sum of CO$_2$ allocation satisfaction in all cities under various values of $a$. The sum of CO$_2$ allocation satisfaction experiences an increase first and then declines continuously, and it peaked when $a$ is close to 0.1 at 26.211. The total CO$_2$ allocation satisfaction is 26.206 when $a$ is equal to 0, which is only a little lower than the peak. When $a$ at high levels (more than 0.2), the sum of CO$_2$ allocation satisfaction is sensitive to increasing value $a$, presenting a faster decrease trend, therefore, it is more likely to obtain a higher level of satisfaction by controlling the value of $a$ at lower levels (less than 0.2). However, it may cause low CO$_2$ allocation satisfaction in some cities. For example, the CO$_2$ allocation satisfaction in Shijiazhuang is 0 in the case of $a=0$. Thus, the policy makers must adopt reasonable minimum CO$_2$ allocation satisfaction to ensure the feasibility of all cities.
5. Conclusions and policy implications

This paper develops a multi-objective decision model integrating the principles of fairness, efficiency, sustainability, and feasibility to allocate the CO₂ emission quotas at the city level. Taking BREC as an example, we formulate the CO₂ emission quotas allocation for 44 cities in 2030. The main findings are as follows:

Results in the case of equal weights show that Beijing, Tianjin, Dalian, Shijiazhuang, Yantai, Weifang, and Linyi enjoy the largest CO₂ emission quotas 1179.94 Mt in total and accounting for 31%. Compared with the initial CO₂ emissions obtained by grandfathering, fifteen out of the 44 cities are found to cut down their CO₂ emission quotas including Langfang, Tangshan, and Cangzhou, while nineteen cities such as Beijing, Qingdao and Yantai have increased their emission quotas in 2030 that can be sellers in the carbon trading market. The emission quotas in the remaining ten cities (Qinhuangdao, Anshan, Fushun, and Benxi) remain stable, compared to initial CO₂ emissions.
The single principle-based allocation results display that the principles of fairness, efficiency, sustainability, and feasibility significantly conflict with each other in most cities. Generally, allocation scheme that considers only single principle tends to be less satisfactory. Fairness and sustainability principles, with low satisfaction of CO₂ emission quotas allocation, apparently partially go against the feasibility. Similarly, the efficiency principle departs from fairness and sustainability, even though it is more feasible. The sustainability principle, which only considers the environmental factors, cannot achieve fair and efficient allocation results.

Compared with the single principles allocation scheme, the multi-objective allocation model performs much better integrating the principles of fairness, efficiency, sustainability and feasibility and effectively avoiding distorting the allocation results. Results in the multi-objective allocation model under various cases show fewer differences from each other. The satisfaction degree function in CO₂ emission quotas allocation ensures the results more reasonable and acceptable. Also, it avoids sacrificing the satisfaction of any city effectively. Furthermore, the multi-objective allocation model provides various available options for policymakers by simply adjusting the weights of each principle. Sensitivity analysis indicates that the total CO₂ allocation satisfaction experiences an increase first and then declines constantly, and it reaches the peak when \(a\) is close to 0.1 at 26.211.

Based on the empirical results, we further put forward several policy implications. First, policymakers need to select reasonable indicators to allocate emission quotas so that it adapts to the development stages of different cities. In addition to focusing on economic
development level, population, and emission efficiency, attention also should be paid to the environmental factors. To achieve the emissions reduction target, for one thing, the local governments should develop and use clean and renewable energy sources. For another, the investment in afforestation should be promoted to improve the CO\textsubscript{2} sequestration capacity.

Second, local governments should formulate targeted policies for emission reduction based on quotas allocation and their situation. The policy orientation must be suitable for the local development. For the cities with heavy emission reduction burden, namely, Langfang, Tangshan, Cangzhou, Handan, Panjin, Liaoyang, and Binzhou, besides developing the economy, the governments should also practice the concept of green development and promote green consumption at both enterprise and individual levels. For the cities with relatively small emission reduction burden, such as Beijing, Dalian, Zhangjiakou, Chaoyang, and Xingtai, technology innovation for energy saving and emissions reduction should be encouraged. For example, promoting carbon capture and storage technologies and optimizing the production process.

Third, the results show that the principles of fairness, efficiency, sustainability, and feasibility are irreconcilable. Thus, policymakers should explore a compromise solution to eliminate the limitations of allocation schemes based on a single principle. The multi-objective allocation model provides options for decision-makers and can be advocated when allocating CO\textsubscript{2} emission quotas at the city level.

Finally, policymakers must pay attention to the relationship between the total CO\textsubscript{2} allocation satisfaction and the individual city’s CO\textsubscript{2} allocation satisfaction. Although a
at low levels can achieve the higher total satisfaction, it is based on sacrificing the satisfaction of some cities. Therefore, it is of critical importance to set the value of \( a \) to make the CO\(_2\) emission quotas allocation for cities more reasonable.

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Declarations

- **Ethics approval and consent to participate**
  Not applicable

- **Consent for publication**
  Not applicable

- **Availability of data and materials**
  The datasets generated and analyzed during the current study are available in the National Bureau of Statistics of China, China Energy Statistics Yearbook, and China City Statistical Yearbook. [http://www.stats.gov.cn/tjsj/ndsj/](http://www.stats.gov.cn/tjsj/ndsj/)

- **Competing interests**
  The authors declare that they have no competing interests

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**Authors’ contributions**
Zhiyuan Li: conceptualization, methodology, software, resources, data curation, writing-original draft, writing-review and editing; Huadun Chen: validation, investigation, resources, data curation, writing-review and editing; Juan Wang: conceptualization, investigation, writing-original draft writing-review and editing; Tao Zhao: methodology, formal analysis, writing-review and editing.