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Carbon Emission Allocation in a Chinese Province-Level Region Based on Two-Stage Network Structures

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Received: 2 February 2019; Accepted: 28 February 2019; Published: 5 March 2019

Abstract: With the increasingly severe global environment and climate change, the growing social attention toward the environmental problems has prompted local governments to make policy adjustments. The formulation of the carbon emission right allocation scheme is important for policy-makers. Many researchers have studied the problem of carbon emission right allocation by using data envelopment analysis (DEA) models. However, the existing literature using traditional models consider each Decision-Making Unit (DMU) as a "black box" without taking the internal structure into account, but in fact, it is more accurate for formulating the scheme when considering the inner operation of DMUs. This paper investigates the allocation plan of carbon emission right among each province in China from 2007–2016 based on a two-stage DEA model. The results indicate that, first, there is no space for carbon emission in the north, northeast, and northwest from 2007–2016, while in the southern regions, it always exists. In addition, the carbon emission permits of the southern and eastern regions are increasing, but in the southwestern regions, the carbon emission space barely fluctuated during this decade. Second, the potential of carbon emission reduction of each region tends to be stable after 2014, and in the north and northwest, it fluctuated greatly from 2007–2016. Besides, the northwest region has had the potential of emission reduction since 2010, while it also exists in the northern region after 2014.

Keywords: data envelopment analysis; carbon emission allocation; two-stage network

1. Introduction

Growing social concerns about the environment with the increasingly severe global environment and climate change are pushing the local government to make policy adjustments [1]. As one of the largest energy consumption and CO_2 emission countries [2,3], China has shown its determination to actively deal with the problem of climate change. At the 2009 Copenhagen climate conference, China made the commitment to reduce the carbon emission per unit of Gross Domestic Product (GDP) by 40–45% compared with 2005 by 2020 [4,5], then in the 2014 Sino-U.S. joint statement on climate to reduce carbon emission intensity by 60–65% compared with 2005 by 2030 [6]. At the end of 2017, the Chinese government announced the launch of a nationwide carbon trading market to achieve energy conservation and emission reduction targets. However, in the process of policy implementation, policymakers not only need to encourage provinces to achieve emission reduction targets, but also have to avoid disturbing market order [7]. Therefore, under the circumstances of the fixed amount of carbon emission right, how to formulate a reasonable and effective scheme of carbon emission right allocation is urgently needed based on the development and the amount of actual carbon emission of each province.

There are many international studies on the distribution of carbon emissions. In 1990, three major initial distribution schemes were proposed in the Amendment for the first time, namely public auction, fixed price sale, and free distribution. Some literature, such as Cramton et al. [8] and Kampas et al. [9], compared the characteristics of these schemes and concluded that each method has its own advantages in different situations. In 2005, the European Union Emissions Trading Scheme (EU ETS), which is the biggest emission trading market, was launched with the aim to achieve a given reduction target for aggregate CO_2 emissions at minimal cost [10,11]. Many scholars have investigated the carbon emission allocation rule in the EU ETS. Martin et al. [12] concluded that EU ETS had a robust negative impact on emission reduction, but no evidence supported the view that the EU ETS had strong detrimental effects on economic performance in exploring whether EU ETS had an impact on the economy. Oestreich et al. [11] and Daskalakis et al. [13] found that there exists a statistically-significant carbon premium in the study of the impact of EU ETS on the financial performance of enterprises. As the world's largest carbon emitter, China faces greater pressure to reduce emissions. Therefore, it is meaningful to investigate the Chinese provincial carbon emission rights allocation. In addition, the experience of Chinese provincial carbon allocation research has significance to other countries in the world because the measures adopted by the Chinese government to allocate the carbon emissions right to each province are similar to those of the European Union Emissions Trading Scheme (EU ETS) to participating countries.

In recent years, Data Envelopment Analysis (DEA), which is an axiomatic non-parametric mathematical programming technique, has been increasingly used to allocate the fixed cost among homogeneous Decision-Making Units (DMUs) [14,15]. The rationale for its popularity in solving the fixed cost allocation problem is that it has several advantages. First, subjectivity can be avoided because there is no need to impose weights on inputs and outputs in advance [16,17]. Second, the DEA model has a high level of computational tractability and practicality since it is formulated and solved by linear programming [18,19]. Third, DEA provides decision-makers the possibility of considering the effect of feasible allocation plans on performance evaluation [20].

In China, there is a large regional imbalance between provinces. These imbalances include natural resources and the structure of economic and energy consumption [21]. Therefore, provinces should shoulder the burdens of carbon emission reduction jointly, but differentially [22,23]. The allocation of carbon emission reduction responsibility is actually the allocation of carbon emission right of each province since each province wants to take on less responsibility for emission reduction. Therefore, the allocation of carbon emission right is equivalent to the allocation of fixed cost.

In terms of allocation principles, DEA-based fixed cost allocation models in the existing literature can be classified into three categories. The first one is the principle of efficiency-invariance proposed by Cook and Kress [24], which assumes that the efficiency score of each DMU should remain unchanged after allocation. However, the method of cost allocation based on the efficiency invariance principle may be determined entirely by the input side of DMUs, namely the amount of cost allocation is the same for DMUs with the same inputs, but different outputs. The second one is the efficiency-maximization approach, first proposed by Beasley [25], which assumes that all DMUs would be efficient after the allocation under a set of common weights. However, the model is non-linear, and the gap between the maximum value and the minimum value in the final allocation scheme is large, which leads to difficulty in implementation. The last one is the game-based approach, first proposed by Nakabayashi and Tone [26]. This principle combines game theory with DMUs, that is the more one side gets, the less others get. In a recent study, Li et al. [27] developed a DEA-game cross-efficiency approach by integrating cooperative game theory and the cross-efficiency to generate a unique and fair allocation plan.

In previous literature, almost all literature dealing with carbon emission allocation with DEA was based on the above three principles. Gomes and Lins [28] proposed a Zero Sum Gains DEA (ZSG-DEA) model based on the input-oriented radial CCR-DEA model to allocate CO_2 emissions allowance among the Annex I parties and Non-Annex I countries of the Kyoto Protocol. Lozano et al. [29] proposed a DEA approach with three phases, i.e., maximizing aggregated desirable production, minimizing undesirable total emissions, and minimizing the consumption of input resources, to reallocate the emission permits. Wei et al. [30] estimated the CO_2 reduction potential and marginal abatement costs for 29 provinces over the period of 1995–2007 by using an extended Slacks-Based Measure (SBM) model. Wang et al. [31] proposed a non-radial ZSG-DEA model for emission allowance allocation on the provincial level for China by 2020. Miao et al. [23] also used a non-radial ZSG-DEA model to allocate CO_2 emissions between different Chinese provinces, but treating CO_2 as the undesirable output variable. Feng et al. [32] proposed a novel method that combined centralized models and compensation schemes for carbon emission abatement allocation. Zhou et al. [33] presented a DEA approach with multiple abatement factors based on the principles of equity and efficiency to allocate CO_2 emission quotas in 71 Chinese cities over 2005–2012. Yu et al. [34] considered the potential collaboration between industrial decision-making units and proposed a nonlinear DEA approach to allocate the regional industrial carbon abatement tasks.

Summarizing the related research, we find that all of the above studies considered each DMU as a "black box" without taking into account the internal structure. However, it is more accurate for formulating the scheme when considering the inner operation of DMUs. As a result, a new DEA model with a network structure was introduced by Färe [35]. There are some studies in the existing literature evaluating the efficiency of DMUs and allocating the fixed cost based on two-stage network DEA approaches, while little work has been done on the fixed cost allocation of practical problems by using the DEA-network model. Wanke et al. [36] adopted a network-DEA centralized efficiency model to measure the efficiency in Brazilian banking. Li et al. [37] used a three-stage DEA model to measure the efficiency of China's manufacturing sector measures on green productivity growth during the 11^{th} Five-Year Period. In addition to efficiency evaluation, some scholars have studied fixed cost allocation based on the two-stage DEA model in recent years. Yu et al. [38] proposed a fixed cost allocation method based on the two-stage network DEA and the cross-efficiency to allocate the fixed cost adequately. Zhu et al. [39] discussed the fixed cost allocation problem by using a two-stage network DEA method and proposed three procedures to obtain a fair cost allocation plan based on different objectives in reality. Ding et al. [40] first presented additive two-stage models to evaluate the performance for each DMU when allocating the fixed cost, and via introducing the concepts of satisfaction degree and fairness degree, an approach was proposed to obtain an optimal allocation plan. However, their approach cannot guarantee a unique allocation plan. Li et al. [41] first used the DEA model to measure the relative efficiency while taking the internal structure and possible allocated costs into account and proposed a unique allocation plan for all DMUs and sub-stages in view of the operation size of each DMU. Although the efficiency values of all DMUs are maximized and the allocation plan is unique, the algorithm of Li et al. [41] is not rigorous, since they neglected the use of the dual solution.

In this paper, we adopt the two-stage DEA-network model based on Li et al. [41] to investigate the allocation plan of carbon emission right among each province in China, and the algorithm for solving the unique allocation scheme is modified to make the result more accurate. To the best of our knowledge, none of the existing literature deals with carbon allocation based on the two-stage DEA-network model. Due to the complexity of the social economic structure in China, it is obviously inaccurate for the allocation plan to use the traditional DEA models that only consider the initial inputs and the final outputs of DMUs to deal with carbon emission right allocation. Nevertheless, a two-stage DEA-network model combines two stages via the intermediate variables, which means that the output of the first stage is the input of the second stage. The total fixed carbon emission will be allocated to each phase to participate in the whole production process. To sum up, the contributions of this paper are three-fold. Firstly, this paper applies the two-stage DEA-network model to investigate the allocation plan of carbon emission right. The two-stage DEA-network model is adopted to investigate the allocation plan of carbon emission right for the first time. Secondly, we point out that the algorithms solving the unique allocation scheme of the existing literature are not rigorous since they neglect the information of the dual solution, so the algorithms are modified in this paper to make the result more accurate. Finally, a fair, effective, and unique allocation plan is generated by combining the two-stage DEA-network model with the practical problem of carbon emission allocation right in China. By means of analyzing the allocation amount in the first and second stage, as well as the carbon emission space and emission reduction potential of each province, some guidance and suggestions can be provided for policy-makers.

The remainder of this paper is organized as follows. In Section 2, the methodology for carbon emission allocation is presented. In Section 3, an empirical analysis of the carbon emission allocation of each province is analyzed based on the two-stage DEA-network models proposed above, as well as the space and potential of carbon emission reduction of different regions in China. Then, some suggestions are given to policy-makers based on the results. Finally, Section 4 presents the main conclusions of the work.

2. Materials and Methods

2.1. Preliminary

DEA was first introduced by Charnes et al. [42] in 1978 and was called the CCR model, which assumed Constant Return to Scale (CRS). Subsequently, it was extended to the BCC model by Banker et al. [43], which assumed Variable Return to Scale (VRS), i.e., inputs and outputs cannot be increased or decreased proportionately. We will briefly describe the classical BCC model in this section.

Suppose there is a set of homogeneous DMUs, and each $DMU_j(j = 1, ..., n)$consumes m inputs $x_{ij}(i = 1, ..., m)$ to produce s outputs $y_{rj}(r = 1, ..., s)$. The relative efficiency score for any given DMU_d is calculated by solving the following BCC model:

$$
\begin{aligned}
&\theta_d^\star = Max \frac{\sum\limits_{r=1}^{s} u_r y_{rd} + u_0}{\sum\limits_{i=1}^{m} v_i x_{id}} \\
&s.t. \quad \frac{\sum\limits_{r=1}^{s} u_r y_{rj} + u_0}{\sum\limits_{i=1}^{m} v_i x_{ij}} \leq 1, \quad \forall j = 1, 2, \ldots, n \\
&u_r, v_i \geq 0, \quad \forall r = 1, 2, \ldots, s; i = 1, 2, \ldots, m
\end{aligned}
\tag{1}
$$

where u_r and v_i are unknown weights attached to the r^{th} output and i^{th} input, respectively, and the optimal objective function $\theta_d^\star$ is defined as the BCC efficiency score of DMU_d; where $u_0 > 0$ represents increasing return to scale, $u_0 < 0$ represents decreasing return to scale, and $u_0 = 0$ represents constant return to scale. Given $u_0 = 0$, then the above model will be transformed to the CCR model.

Model (1) is nonlinear in a fractional programming form, and it can be transformed to a linear model by the Cooper–Charnes transformation. Let $t = 1/\sum\limits_{i=1}^{m} v_i x_{id}$, $\mu_r = tu_r$, $v_i = tv_i$, $\mu_0 = tu_0$. Then, the model becomes:

$$
\begin{aligned}
&\theta_d^\star = Max \sum_{r=1}^{s} \mu_r y_{rd} + \mu_0 \\
&\text{s.t.} \quad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + \mu_0 \geq 0, \quad \forall j = 1,2,\ldots,n \\
&\sum_{i=1}^{m} v_i x_{id} = 1 \\
&\mu_r, v_i \geq 0, \quad \forall r = 1,2,\ldots,s; i = 1,2,\ldots,m
\end{aligned}
\tag{2}
$$

Solving Model (2), a series of weights $(\mu_r^\star, v_i^\star, \mu_0^\star)$ and the efficiency value of each DMU are obtained. The efficiency of DMU_d is $\theta_d^\star = \sum_{r=1}^{s} \mu_r^\star y_{rd} + \mu_0^\star$, which ranges from zero to one, and DMU_d is identified as DEA efficient if $\theta_d^\star = 1$, otherwise DEA inefficient.

2.2. Carbon Emission Right Allocation Model Based on Two-Stage Structures

2.2.1. Two-Stage Network Structure

Consider the two-stage network structure shown in Figure 1.

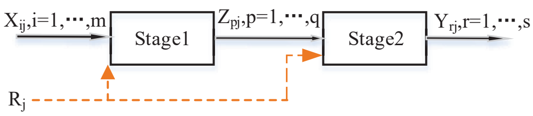

Figure 1. Two-stage network process of DMU_j.

In the first stage, the inputs of DMU_j are $x_{ij}(i = 1,\ldots,m)$, and the outputs are the intermediate variables $z_{pj}(p = 1,\ldots,q)$. In the second stage, the intermediate variables z_{pj} are taken as inputs to produce the final outputs $y_{rj}(r = 1,\ldots,s)$.

Suppose that there exists a total fixed cost R to be allocated, and the amount of allocation to each DMU_j is R_j, i.e.,

$$\sum_{j=1}^{n} R_j = R, R_j \geq 0, \quad \forall j = 1,2,\ldots,n \tag{3}$$

The allocation amount R_j of each DMU_j is allocated to the first stage and the second stage to participate in production activities with R_{1j} and R_{2j}, respectively, such that:

$$R_j = R_{1j} + R_{2j}, R_{1j} \geq 0, R_{2j} \geq 0, \quad \forall j = 1,2,\ldots,n \tag{4}$$

Based on the two-stage DEA model [41], we obtain the following model to calculate the overall efficiency when $DMU_d(d = 1,\ldots,n)$ is under evaluation:

$$\begin{aligned}
&\theta_d^\star = Max\frac{\sum\limits_{p=1}^{q}\varphi_p z_{pd}+\varphi_0+\sum\limits_{r=1}^{s}\mu_r y_{rd}+\mu_0}{\sum\limits_{i=1}^{m}v_i x_{id}+v_{m+1}R_{1d}+\sum\limits_{p=1}^{q}\varphi_p z_{pd}+v_{m+1}R_{2d}}\\
&\text{s.t.}\quad \theta_{1j}=\frac{\sum\limits_{p=1}^{q}\varphi_p z_{pj}+\varphi_0}{\sum\limits_{i=1}^{m}v_i x_{ij}+v_{m+1}R_{1j}}\le 1,\quad \forall j=1,2,\ldots,n\\
&\theta_{2j}=\frac{\sum\limits_{r=1}^{s}\mu_r y_{rd}+\mu_0}{\sum\limits_{p=1}^{q}\varphi_p z_{pj}+v_{m+1}R_{2j}}\le 1,\quad \forall j=1,2,\ldots,n\\
&\sum_{j=1}^{n}R_{1j}+R_{2j}=R, R_{1j},R_{2j}\ge 0,\quad \forall j=1,2,\ldots,n\\
&\mu_r,\varphi_p,v_i\ge 0,\quad \forall r=1,\ldots,s; p=1,\ldots,q; i=1,\ldots,m
\end{aligned}\tag{5}$$

where θ_{1j} and θ_{2j} are the efficiency values of DMU_j in the first stage and the second stage, respectively, and $\theta_d^\star$ is the overall efficiency of the DMU_d to be evaluated. It is noteworthy that the overall efficiency $\theta_d^\star$ can be represented by a combination of θ_{1d} and θ_{2d}, namely $\theta_d^\star = \lambda_d^1\theta_{1d}+\lambda_d^2\theta_{2d}$. λ_d^1 and λ_d^2 represent the relative importance of Sub-stages 1 and 2, respectively. It can be measured by the proportion of inputs in each stage on the total inputs, that is,

$$\begin{aligned}
\lambda_d^1 &= \frac{\sum_{i=1}^{m}v_i x_{id}+v_{m+1}R_{1d}}{\sum_{i=1}^{m}v_i x_{id}+v_{m+1}R_{1d}+\sum_{p=1}^{q}\varphi_p z_{pd}+v_{m+1}R_{2d}},\\
\lambda_d^2 &= \frac{\sum_{p=1}^{q}\varphi_p z_{pd}+v_{m+1}R_{2d}}{\sum_{i=1}^{m}v_i x_{id}+v_{m+1}R_{1d}+\sum_{p=1}^{q}\varphi_p z_{pd}+v_{m+1}R_{2d}}
\end{aligned}$$

Model (5) is fractional programming, so we need to transform it to a linear model (6) (see Appendix A for details).

$$\begin{aligned}
&\theta_d^\star = Max(\sum_{p=1}^{q}\phi_p z_{pd}+\phi_0+\sum_{r=1}^{s}u_r y_{rd}+u_0)\\
&\text{s.t.}\quad \sum_{p=1}^{q}\phi_p z_{pj}+\phi_0-\sum_{i=1}^{m}v_i x_{ij}-r_{1j}\le 0,\quad \forall j=1,2,\ldots,n\\
&\sum_{r=1}^{s}u_r y_{rj}+u_0-\sum_{p=1}^{q}\phi_p z_{pj}-r_{2j}\le 0,\quad \forall j=1,2,\ldots,n\\
&\sum_{i=1}^{m}v_i x_{id}+r_{1d}+\sum_{p=1}^{q}\phi_p z_{pd}+r_{2d}=1\\
&\sum_{j=1}^{n}(r_{1j}+r_{2j})=v_{m+1}R, r_{1j},r_{2j}\ge 0,\quad \forall j=1,2,\ldots,n\\
&u_r,\phi_p,v_i\ge 0, v_{m+1}>0,\quad \forall r=1,\ldots,s; p=1,\ldots,q; i=1,\ldots,m
\end{aligned}\tag{6}$$

For DMU_d, the optimal weights of the model are $(u_r^{d\star},\phi_p^{d\star},v_i^{d\star},v_{m+1}^{d\star},r_{1j}^{d\star},r_{2j}^{d\star},\phi_0^{d\star},u_0^{d\star})$, and the optimal value can be calculated by $\theta_d^\star=\sum_{p=1}^{q}\phi_p^{d\star}z_pd+\phi_0^{d\star}+\sum_{r=1}^{s}u_r^{d\star}y_{rd}+u_0^{d\star})$. In addition, the fixed cost allocation plan from the perspective of DMU_d is $R_j^{d\star} = R_{1j}^{d\star} + R_{2j}^{d\star} (j = 1, \ldots, n)$, where $R_{1j}^{d\star} = r_{1j}^{d\star} / v_{m+1}^{d\star}$ and $R_{2j}^{d\star} = r_{2j}^{d\star} / v_{m+1}^{d\star}$.

Li et al. [41] proved that there exists at least a set of weights to make all DMUs and their sub-stage be simultaneously efficient. Therefore, an efficient allocation plan can be obtained as follows:

$$
\begin{aligned}
&\sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1, 2, \ldots, n \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1, 2, \ldots, n \\
&\sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
&u_r, \phi_p, v_i \geq 0, \quad \forall r = 1, 2, \ldots, s; p = 1, 2, \ldots, q; i = 1, 2, \ldots, m
\end{aligned} \tag{7}
$$

It can be seen from the efficient allocation plan (7) that the weights attached to the allocated cost are meaningless; for simplicity, the weight is usually set to one [25]. In the efficient allocation plan (7), there are $(m + q + s + 2n + 2)$ variables, but only $(2n + 1)$ equality constraints. Therefore, the solution of (7) may not be unique.

2.2.2. Carbon Emission Right Allocation Based on the Two-Stage DEA Model

In this subsection, we obtain a unique allocation plan by taking the operation size of each DMU into consideration. Miao et al. [23] pointed out in the study of regional carbon emission allocation in China that the carbon emission allocation right based on per capita carbon emission would expand the gap between provinces. Specifically, for some developed regions, such as Beijing and Shanghai, their population is relatively less than that of underdeveloped provinces, but they produce more carbon emission. If the allocation is carried out according to per capita carbon emission, each province will not be efficient, and the disadvantage of allocating based on emission per unit of GDP is that it will restrict the development of some relatively underdeveloped provinces. Similar literature include Zhang et al. [44], Zhou et al. [7], and Kong et al. [45]. Therefore, various factors need to be taken into account to allocate the carbon emission rights of all provinces in China equitably and effectively.

This paper formulates a unique allocation plan based on the size of DMUs; it is reasonable and acceptable to allocate a large amount of carbon emission right to DMUs with large inputs and outputs and a small amount to DMUs with small inputs and outputs. Suppose the size parameters of the first stage and second stage are α_j and β_j, respectively. Then, the total amount of carbon emission allocation right of DMU_j will be allocated to each stage by $\alpha_j R$, $\beta_j R$, and $\sum_{j=1}^{n} (\alpha_j + \beta_j) = 1$. The data processing and the operation size parameters are presented in Appendix B.

In order to obtain a unique allocation plan, we need to introduce a series of deviation variables that measure the difference between the efficient allocation R_{1j} and R_{2j} given in (7) and the proportionate allocation $\alpha_j R$ and $\beta_j R$.

Let $|\alpha_j R - R_{1j}| = C_j$ and $|\beta_j R - R_{2j}| = D_j$, that is C_j represents the deviation between R_{ij} and $\alpha_j R$ for the first stage and D_j represents the deviation between R_{2j} and $\beta_j R$ for the second stage, and both C_j and D_j should be minimized. To this end, we minimize the maximum combined deviation $(C_j + D_j)$. The model (8) is as follows:

$$\begin{aligned}
&MinMax(C_k + D_k) \\
&\text{s.t.} \quad \left|\alpha_j R - R_{1j}\right| = C_j, \quad \forall j = 1,2,\ldots,n \\
&\left|\beta_j R - R_{2j}\right| = D_j, \quad \forall j = 1,2,\ldots,n \\
&\sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1,2,\ldots,n \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1,2,\ldots,n \\
&\sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1,2,\ldots,n \\
&u_r, \phi_p, v_i \geq 0, \quad \forall r = 1,2,\ldots,s; p = 1,2,\ldots,q; i = 1,2,\ldots,m
\end{aligned} \tag{8}$$

In Model (8), the objective function is the deviation, and the value should be as small as possible. The first and the second constraints represent the deviation of each stage, and the subsequent constraints are the efficient allocation set. Since the model (8) is nonlinear, we need to change it into a linear model (9) (see Appendix C for details).

$$\begin{aligned}
&MinMax \quad \rho \\
&\text{s.t.} \quad c_{1j} + c_{2j} + d_{1j} + d_{2j} - \rho_j = 0, \quad \forall j = 1,2,\ldots,n \\
&\rho_j - \rho \leq 0, \quad \forall j = 1,2,\ldots,n \\
&\alpha_j R - R_{1j} = c_{1j} + c_{2j} \quad \forall j = 1,2,\ldots,n \\
&\beta_j R - R_{2j} = d_{1j} - d2j, \quad \forall j = 1,2,\ldots,n \\
&\sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1,2,\ldots,n \\
&\sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1,2,\ldots,n \\
&\sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1,2,\ldots,n \\
&c_{1j}, c_{2j}, d_{1j}, d_{2j} \geq 0, \quad \forall j = 1,2,\ldots,n \\
&u_r, \phi_p, v_i \geq 0, \quad \forall r = 1,2,\ldots,s; p = 1,2,\ldots,q; i = 1,2,\ldots,m
\end{aligned} \tag{9}$$

2.2.3. Algorithm for Solving the Above Model

Suppose the optimal weights of the model (9) are $(\rho^{1\star}, c_{1j}^{1\star}, c_{2j}^{1\star}, d_{1j}^{1\star}, d_{2j}^{1\star}, \rho_j^{1\star}, u_r^{1\star}, \phi_p^{1\star}, v_i^{1\star}, R_{1j}^{1\star}, R_{2j}^{1\star}, \phi_0^{1\star}, u_0^{1\star}, \forall j, r, p, i)$. The allocation plans can be affected if we neglect the fact that the model (9) may have multiple optimal solutions and ignoring the information provided by the dual problem. Therefore, we need to use the dual programming of the model (9). The duality problem is formulated below.

$$
\begin{aligned}
& max \sum_{j=1}^{n} h_j \alpha_j R + \sum_{j=1}^{n} k_j \beta_j R + wR \\
& \text{s.t.} \quad \sum_{j=1}^{n} g_j \leq 1 \\
& f_j + h_j \leq 0, \quad \forall j = 1,2,\ldots,n \\
& f_j - h_j \leq 0, \quad \forall j = 1,2,\ldots,n \\
& f_j + k_j \leq 0, \quad \forall j = 1,2,\ldots,n \\
& f_j - k_j \leq 0, \quad \forall j = 1,2,\ldots,n \\
& f_j + g_j \geq 0, \quad \forall j = 1,2,\ldots,n \\
& \sum_{j=1}^{n} t_j y_{rj} \leq 0, \quad \forall r = 1,2,\ldots,s \\
& \sum_{j=1}^{n} l_j z_{pj} - \sum_{j=1}^{n} t_j z_{pj} \leq 0, \quad \forall p = 1,2,\ldots,q \\
& \sum_{j=1}^{n} l_j x_{ij} \geq 0, \quad \forall i = 1,2,\ldots,m \\
& h_j - l_j + w \leq 0, \quad \forall j = 1,2,\ldots,n \\
& k_j - t_j + w \leq 0, \quad \forall j = 1,2,\ldots,n \\
& \sum_{j=1}^{n} l_j \leq 0 \\
& \sum_{j=1}^{n} t_j \leq 0 \\
& f_j, g_j, h_j, k_j, l_j, t_j \geq 0, \quad \forall j = 1,2,\ldots,n \\
& w \geq 0
\end{aligned}
\tag{10}
$$

Based on duality theory, when the optimal value of a dual variable is positive, the inequality constraints associated with this variable in the original problem will hold with equality [46]. By solving the dual model, the DMU_j that satisfies the equation $\rho_j = \rho^{1\star}$ will be determined based on the sign of the corresponding variable c_j being positive. Then, all DMUs can be divided into two subsets:

$$
\Gamma_1 = \left\{ j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} = \rho^{1\star} \right\}, \quad \Gamma_2 = \left\{ j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} < \rho^{1\star} \right\} \tag{11}
$$

then minimizing the deviations of DMUs in Γ_2. The process will not be terminated until the minimum deviation has been determined for all DMUs. The algorithm flow is described as follows:

Step 1: Let $t = 1$, solving the model (9) to obtain the optimal weights $(\rho^{1\star}, c_{1j}^{1\star}, c_{2j}^{1\star}, d_{1j}^{1\star}, d_{2j}^{1\star}, \rho_j^{1\star}, u_r^{1\star}, \phi_p^{1\star} v_i^{1\star}, R_{1j}^{1\star}, R_{2j}^{1\star}, \phi_0^{1\star}, u_0^{1\star}, \forall j, r, p, i)$. If the deviation $\rho_j = c_{1j} + c_{2j} + d_{1j} + d_{2j}$ of DMU_j is equal to $\rho^{1\star}$, then we solve the dual model to determine whether the corresponding dual variable c_j of DMU_j is positive. If $c_j > 0$, then the DMU_j is a member of set $\Gamma_1 = \{j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} = \rho^{1\star}\}$, and the allocation plan of DMU_j can be determined as $R_{1j}^{\star}$ and $R_{2j}^{\star}$; otherwise, the DMU_j with other DMU_j whose deviations are not equal to $\rho^{1\star}$ will be regarded as members of set Γ_2, i.e., $\Gamma_2 = \{j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} < \rho^{1\star}\}$. Denote the number of DMUs in Γ_1 as n_1.

Step 2: If $n_1 = m + q + s + 1$ (the number of flexible variables in the efficient allocation set (7) is $(m + q + s + 1)$), then the algorithm terminates, and the final allocation plan is uniquely given by $(R_{1j}^{\star}, R_{2j}^{\star}, \forall j)$. Otherwise, go to Step 3 if $n_1 < m + q + s + 1$.

Step 3: Let $t = t + 1$, solving the model (12) to obtain the optimal weight $(\rho^{(t+1)\star}, c_{1j}^{(t+1)\star}, c_{2j}^{(t+1)\star}, d_{1j}^{(t+1)\star}, d_{2j}^{(t+1)\star}, \rho_j^{(t+1)\star}, u_r^{(t+1)\star}, \phi_p^{(t+1)\star}, v_i^{(t+1)\star}, R_{1j}^{(t+1)\star}, R_{2j}^{(t+1)\star}, \phi_0^{(t+1)\star}, u_0^{(t+1)\star}, \forall j, r, p, i)$.

$$
\begin{aligned}
& Min \quad \rho \\
& \text{s.t.} \quad c_{1j} + c_{2j} + d_{1j} + d_{2j} - \rho_j = 0, \quad \forall j = 1, 2, \ldots, n \\
& \rho_j = \rho^{1\star}, \quad \forall j \in \Gamma_1 \\
& \vdots \\
& \rho_j = \rho^{(t-1)\star}, \quad \forall j \in \Gamma_{2t-1} \\
& \rho_j - \rho \leq 0, \quad j \in \Gamma_{2t} \\
& \alpha_j R - R_{1j} = c_{1j} + c_{2j} \quad \forall j = 1, 2, \ldots, n \\
& \beta_j R - R_{2j} = d_{1j} - d2j, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& c_{1j}, c_{2j}, d_{1j}, d_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& u_r, \phi_p, v_i \geq 0, \quad \forall r = 1, 2, \ldots, s; p = 1, 2, \ldots, q; i = 1, 2, \ldots, m
\end{aligned}
\tag{12}
$$

If the deviation of DMU_j is equal to $\rho^{(t+1)\star}$, then we solve the dual programming of the model (12) in the same way to determine whether the corresponding dual variable c_j of DMU_j is positive. If $c_j > 0$, then the DMU_j is a member of set Γ_{2t+1}, and the allocation plan of DMU_j can be determined as $R_{1j}^{(t+1)\star}$ and $R_{2j}^{(t+1)\star}$; otherwise, the DMU_j with other DMU_j whose deviations are not equal to $\rho^{(t+1)\star}$ will be regarded as members of set Γ_{2t+2}. Then, the set Γ_{2t} is divided into two subsets as follows: $\Gamma_{2t+1} = \left\{ j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} = \rho^{(t+1)\star} \right\}$, $\Gamma_{2t+2} = \left\{ j \mid c_{1j} + c_{2j} + d_{1j} + d_{2j} < \rho^{(t+1)\star} \right\}$. Denote the number of DMUs in Γ_{2t+1} as n_{t+1}.

Step 4: If $n_1 + n_2 + \ldots + n_{t+1} = m + q + s + 1$, then the algorithm terminates, and the final allocation plan is determined by $(R_{1j}^{(t+1)\star}, (R_{2j}^{(t+1)\star}, \forall j)$. Otherwise, go to Step 3 to continue.

3. Results and Discussion

The data source, allocation results, and some policy suggestions are presented in this section.

3.1. Variables and Data

By reviewing the principle of CO_2 emissions quota allocation in present studies, it can be seen that allocation principles of CO_2 emissions right are often based on economic ability, historical carbon emissions levels, and energy consumption, as well as some other indicators. For example, Wang et al. [31] considered population, total energy consumption, and CO_2 emissions as inputs and GDP as the only output. Feng et al. [32], Miao et al. [23], and Kong et al. [45] regarded labor, capital stock, and total energy consumption as inputs, GDP as the desirable output, and CO_2 emissions as the undesirable output. Jiang et al. [47] concluded that human economic activities in China were the dominant effect of carbon emission, while energy intensity and population growth were the most significant driving force. Wang et al. [48] and Ma et al. [49] indicated that the increase of carbon emission was basically promoted by aggressive economic output and increased energy consumption since the Chinese economy highly depends on energy consumption, and CO_2 emissions from energy consumption mainly came from the residential consumption sector and transportation industry. Therefore, it is reasonable to take the improvement of resident living standards in cities and transportation into account. In this paper, two indicators of urbanization level and private car ownership were selected as intermediate variables to measure the impact of residential consumption and transportation on carbon emission and the economy, respectively. In addition, like most literature, we use capital stock (K), labor force (L), and energy consumption (E) as inputs in the first stage, while GDP as the final desirable output. The following Figure 2 shows the detailed inputs and outputs of the system.

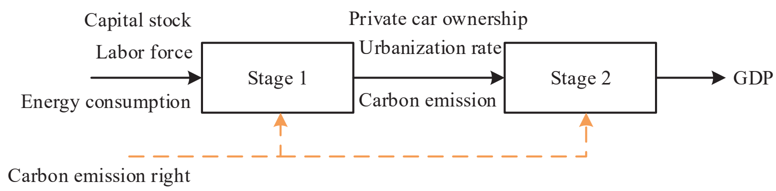

Figure 2. Two-stage network process for carbon emission right allocation.

Dealing with undesirable outputs is also a problem that many scholars have studied in the DEA field. For example, the Directional Distance Function (DDF model, Chung et al. [50]) assumes that undesirable outputs are imposed with weak disposability and DMUs follow a predetermined direction to approach the effective frontier. The limitations of this model are that a directional vector needs to be specified beforehand, and a different final value results from different choices of directional vectors. The hyperbolic model (Färe et al. [51]) also assumes that the undesirable outputs are imposed with weak disposability. Unlike the DDF model, the locus of DMUs moving to the effective frontier in this model is hyperbolic, i.e., the inefficiency is measured by expanding the desirable outputs and reducing undesirable outputs by the same proportion. The limitation of this model is that it is difficult to solve since the model is nonlinear. The Seiford and Zhu model (SZ model, Seiford and Zhu [52]) assumes that undesirable outputs are imposed with strong disposability and transformed by adding a positive scalar on original undesirable outputs after multiplying them by -1. The limitation of this model is that the positive scalar is hard to specify since different transfer vectors will result in different efficiency values. The Undesirable Output as the Input model (UINP model, Hailu and Veeman. [53]) treats undesirable outputs as inputs, but this model cannot accurately represent the production process. In this paper, we adopted the approach consistent with most of the literature on fixed cost allocation dealing with undesirable outputs for simplicity, namely regarding undesirable outputs as inputs.

As an undesirable output, we regarded CO_2 emission as an input in the first stage since DMUs are expected to minimize their input consumption, as well as undesirable outputs.

The data covered 30 provinces during the period 2007–2016. However, Tibet was excluded due to the absence of energy consumption data. Data were collected from the China Statistical Yearbook 2007–2016. The description and processing of variables are as follows:

In terms of capital stock, this refers to all existing resources in provinces, and it is a comprehensive index reflecting the scale, speed, and structure of social investment (Wang et al. [54]). The capital stock is unavailable in any Statistical Yearbook. Therefore, we have to estimate this indicator via using the following method:

$$K_{i,t} = I_{i,t} + (1 - \delta_t)K_{i,t-1} \tag{13}$$

where $I_{i,t}$, δ_i, and $K_{i,t}$ represent gross investment, depreciation rate, and capital stock for province i at time t, respectively. This paper adopted the method of Zhang et al. [55] to set $\delta = 9.6\%$. Furthermore, we extended the capital stock of each province to 2016 based on 2005.

In terms of labor force, this is one of the indicators that must be considered in the production process. This paper selected the number of employees in the urban unit as the labor force indicator, since they are the main contributors of GDP and carbon emission.

As for energy consumption, this is the main contribution of China's economic development. Besides, carbon emission is mainly generated by the burning of fossil energy. Therefore, energy consumption was taken as an input.

For carbon emission, it needed to be estimated since it was not available in existing data sources. At present, there are three international principles for carbon emission accounting [56]. The first one is producer responsibility, i.e., the responsibility of carbon emission belongs to the producers; the second principle is the consumer responsibility, which blames CO_2 emission on consumption; and the third one is a compromise between the first and the second principles, i.e., we need to consider the economic structure of the provinces when calculating carbon emission. Although the third one is more equitable, it was difficult for us to collect data because the China regional input-output table is investigated every five years. Therefore, this paper attributed carbon emissions to producers and believes that the carbon emissions of each province was mainly generated by the consumption of fossil energy in the province [57]. These can be estimated by multiplying the total amounts of energy consumptions by their corresponding carbon emission coefficients [54]. The carbon emission coefficients were obtained from the Intergovernmental Panel on Climate Change 2006. The calculation formula is as follows [30]:

$$CO_2 = \sum_{i=1}^{6} E_i \times CF_i \times CC_i \times COF_i \times \frac{44}{12} \tag{14}$$

where i represents different fossil energy indicators, which includes coal, gasoline, kerosene, diesel, fuel oil, and natural gas. E_i represents the total energy consumption of type i. CF_i represents the carbon emission factor of the ith energy. CC_i is the net calorific value of the ith energy source. COF_i is the carbon oxidation factor, and $\frac{44}{12}$ is the ratio of the mass of one carbon atom combined with two oxygen atoms to the mass of one oxygen atom. The net calorific value and carbon emission factor can be obtained from IPCC 2006, as shown in Table 1. The carbon oxidation factor of each energy defaults to one.

Table 1. Carbon emission coefficients.

Energy Types	The Net Calorific Value		Carbon Emission Factors
	Unit	Value	
coal	kJ/kg	20,908	25.8
gasoline	kJ/kg	43,070	18.9
kerosene	kJ/kg	43,070	19.5
diesel	kJ/kg	42,652	20.2
fuel oil	kJ/kg	41,816	21.1
natural gas	kJ/m^3	38,931	15.3

The urbanization level of each province can reflect people's consumption patterns, which are closely related to carbon emissions and GDP. The index is measured by the ratio of urban population to total population.

With the upgrading of residents' consumption patterns, the purchasing of private cars showed a trend of rapid growth. The ownership of private cars not only reflects economic development and consumption level, but also relates to carbon emission due to the change of travel mode.

This paper took GDP as the only desirable output. In case of the same input from each province, it is believed that the higher the GDP is, the higher the efficiency value the province obtains. Descriptive statistics of the input and output indicators for 30 provinces appear in Table 2, which contains the average level, the standard variance, the minimum level, and the maximum level. Note in Table 2 that the large standard deviation of each input index indicates that there is a great gap between provinces. Therefore, the VRS DEA model was adopted in this paper.

Table 2. Descriptive statistics of the input and output levels for 30 provinces in 2016.

Descriptive Statistics	Average	SD	Maximum	Minimum
Capital stock	91,033.16	56,517.92	237,203.21	14,362.83
Labor force	595.22	423.18	1957.57	63.09
Energy consumption	15,665.73	11,388.68	47,772.59	1393.82
Carbon emission	32,617.88	23,409.29	102,669.79	3139.03
Urbanization rate	0.59	0.11	0.88	0.44
Private car ownership	543.30	401.75	1550.65	72.96
GDP	25,963.95	19,937.99	80,854.91	2572.49

To facilitate the analysis, 30 provinces in China were divided into six regions including north, northeast, east, south, southwest, and northwest according to their geographical division. The north contained five provinces: Beijing, Tianjin, Hebei, Shanxi, and Inner Mongolia. The northeast included three provinces: Liaoning, Jilin, and Heilongjiang. The east included seven provinces: Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, and Shandong. The south included six provinces: Henan, Hubei, Hunan, Guangdong, Guangxi, and Hainan. The southwest involved five provinces: Chongqing, Sichuan, Guizhou, Yunnan, and Tibet. The northwest was comprised of five provinces: Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. In order to put the different indicators of different regions together to compare the differences, this paper simultaneously reduced the asset stock, energy consumption, CO_2 emission, and GDP by 100-times because of the great difference between the indicators. The differences in input and output indicators among different regions are shown in Figure 3.

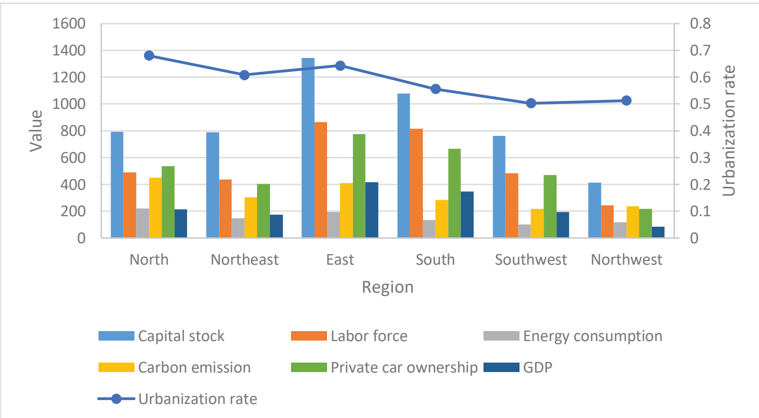

Figure 3. The differences between each region in 2016.

As shown in Figure 3, GDP was relatively large in the eastern and southern regions, while it varied little in the northern, northeastern, and southwestern regions, and it was smallest in the northwest. At the same time, other indicators such as labor force, private car ownership, and capital stock showed the same trend as GDP in each region. This phenomenon was caused by the relatively developed economy and technology in the east and south of China, while the relatively undeveloped situation in the northwest. Energy consumption and CO_2 emission in the north and east were higher, but in the southwest and northwest, they were less since economic development in the north and northeast mainly depends on heavy industry and energy utilization. As for the southwest and northwest, such as Yunnan, Gansu, and Ningxia, there were less energy consumption and CO_2 emissions because of the sparse population and tourism. The urbanization rate was higher in the north, northeast, and east, while it was lower in the south, southwest, and northwest, but they all exceeded 0.5. According to the analysis above, the efficiency evaluation of each province needs to take all the above indicators into account.

3.2. Results Analysis

In order to analyze the carbon emission right allocation of each province, this paper took data into the model (2) and the model (6), respectively, to obtain the efficiency before allocation by setting the fixed cost allocation $R = 0$, and the results are shown in Table 3.

Table 3. The efficiency values of the provinces before the allocation.

Province	BCC.Eff [a]	BCC.Rank	Stage1.Eff [b]	Stage2.Eff [c]	Overall.Eff [d]	Overall.Rank
Beijing	1	1	1	0.7692	0.9054	4
Tianjin	1	1	0.8143	0.7657	0.7925	6
Hebei	0.9557	22	1	0.3016	0.6508	21
Shanxi	0.7910	29	0.8932	0.3478	0.6359	23
Inner Mongolia	1	1	0.7613	0.5136	0.6542	20
Liaoning	0.7551	30	0.6601	0.4358	0.5709	30
Jilin	0.9067	26	0.7202	0.5513	0.6495	22
Heilongjiang	0.8761	27	0.7374	0.5474	0.6568	19
Shanghai	1	1	0.7380	1	0.8493	5
Jiangsu	1	1	0.6786	0.6543	0.6688	17
Zhejiang	0.9399	24	0.9835	0.4487	0.7183	8
Anhui	0.9463	23	0.6825	0.4840	0.6020	27
Fujian	1	1	0.7258	0.6153	0.6793	14
Jiangxi	0.9705	20	0.6746	0.5753	0.6346	24
Shandong	1	1	0.8043	0.4748	0.6574	18
Henan	1	1	0.7119	0.4312	0.5952	28
Hubei	1	1	0.6306	0.6068	0.6214	26
Hunan	1	1	0.7738	0.5638	0.6822	13
Guangdong	1	1	0.9744	0.5853	0.7824	7
Guangxi	1	1	0.8263	0.5372	0.6955	10
Hainan	1	1	1	0.9718	1	1
Chongqing	0.9596	21	0.6763	0.6671	0.6726	15
Sichuan	1	1	0.9937	0.3962	0.6959	9
Guizhou	1	1	0.8006	0.5387	0.6841	12
Yunnan	1	1	1	0.3871	0.6936	11
Shaanxi	0.8729	28	0.6297	0.5072	0.5823	29
Gansu	1	1	0.7045	0.6200	0.6696	16
Qinghai	1	1	1	1	1	1
Ningxia	1	1	1	0.8954	0.9510	3
Xinjiang	0.9394	25	0.7067	0.5302	0.6336	25

[a] BCC.Eff: BCC Efficiency; [b] Stage 1.Eff: Stage 1 Efficiency; [c] Stage2.Eff: Stage 2 Efficiency; [d] Overall.Eff: Overall.Efficiency.

Experimental results show that when using the BCC model for efficiency evaluation, the efficiency of 19 provinces reached one, and all provinces exceeded 0.9 except for seven provinces, including Shanxi, Liaoning, Heilongjiang, Shaanxi, etc. While using the two-stage network model to evaluate the efficiency of provinces, there only Hainan and Qinghai provinces reached the efficiency value of one, followed by Ningxia, Beijing, Shanghai, Tianjin, Guangdong, Zhejiang, etc. This is because each DMU will chose a weight that was most advantageous to itself to achieve maximum efficiency when using the BCC model for efficiency evaluation [58], videlicet the traditional BCC model usually overestimated the efficiency of DMUs and neglected the internal structure of DMUs via only considering the inputs and outputs. By contrast, with some inputs as internal variables, the two-stage network model not only reflected the efficiency of each phase, but also the actual production situation.

This paper first used the method mentioned above to analyze the carbon distribution in each province in 2016. In 2016, the total carbon emission, namely fixed cost allocation, was 978,536.52 tons. Firstly, the model (6) was used to calculate the efficiency of the two subsystems and the overall efficiency after allocation. The result shows that the sub-stages and overall efficiency values of each province were one. Then, we used the model (9) to get the amount of allocation of each subsystem, and finally, the overall allocation was obtained, as shown in Table 4.

Table 4. Carbon emission right allocation in 2016.

Province	Actual Carbon Emissions	Stage 1 Allocation	Stage 2 Allocation	Overall Allocation	Carbon Emission Space
Beijing	5825.54	9220.17	11,844.07	21,064.24	15,238.69
Tianjin	10,918.08	10,014.64	10,111.02	20,125.66	9207.58
Hebei	60,150.40	47,892.50	1088.81	48,981.31	−11,169.09
Shanxi	73,066.16	23,885.34	79.16	23,964.50	−49,101.66
Inner Mongolia	75,158.71	25,141.85	7356.64	32,498.49	−42,660.23
Liaoning	40,263.77	26,521.46	6550.22	33,071.68	−7192.09
Jilin	20,477.66	13,092.27	5993.15	19,085.42	−1392.23
Heilongjiang	30,376.18	13,555.96	5683.94	19,239.90	−11,136.28
Shanghai	16,686.64	6331.69	19,833.42	26,165.10	9478.46
Jiangsu	62,239.03	54,698.20	42,451.31	97,149.51	34,910.48
Zhejiang	34,570.89	38,748.05	16,548.67	55,296.71	20,725.82
Anhui	34,802.07	24,804.37	10,418.32	35,222.69	420.61
Fujian	17,400.95	16,955.25	16,313.37	33,268.62	15,867.68
Jiangxi	17,773.41	14,345.57	8871.92	23,217.49	5444.08
Shandong	102,669.79	71,214.80	25,463.87	96,678.67	−5991.12
Henan	51,235.04	41,066.02	13,592.93	54,658.96	3423.92
Hubei	28,889.45	23,236.92	18,089.68	41,326.60	12,437.15
Hunan	27,141.81	23,832.39	16,556.78	40,389.17	13,247.37
Guangdong	44,437.55	44,489.44	39,439.08	83,928.52	39,490.97
Guangxi	15,978.49	14,217.72	8184.25	22,401.96	6423.48
Hainan	3139.03	206.16	1568.58	1774.75	−1364.29
Chongqing	13,991.02	10,921.45	9613.73	20,535.17	6544.15
Sichuan	24,729.43	29,454.77	11,626.97	41,081.74	16,352.31
Guizhou	29,718.19	11,652.60	3631.38	15,283.99	−14,434.20
Yunnan	18,010.10	16,016.66	1576.54	17,593.20	−416.90
Shaanxi	41,315.73	20,707.80	7241.73	27,949.53	−13,366.19
Gansu	14,272.06	6183.35	1847.25	8030.61	−6241.46
Qinghai	4557.27	61.23	584.19	645.42	−3911.84
Ningxia	17,931.76	3150.05	165.03	3315.07	−14,616.68
Xinjiang	40,810.31	12,048.27	2543.59	14,591.85	−26,218.45

The second column of Table 4 shows the actual carbon emissions of the provinces in 2016, among which the top five provinces for carbon emission were Shandong, Inner Mongolia, Shanxi, Jiangsu, and Hebei. In other words, carbon emission in the northern and eastern regions was relatively higher due to more energy consumption in the northern area and more labor force in the eastern. Based on the two-stage network DEA model proposed in this paper, the top five provinces with the highest carbon allocation were Jiangsu, Shandong, Guangdong, Zhejiang, and Henan, which indicates that the allocation plan was not only related to carbon emissions, but also related to factors such as labor force, asset stock, urbanization rate, and private car ownership.

The last column in the Table 4 is the space of carbon emission that was attained based on the difference between the carbon allocation and actual emission of each province. The space of carbon emission reflects the maximum amount of CO_2 that each province can emit. If the value is negative, this indicates that the corresponding province should improve energy efficiency and reduce CO_2 emission. Otherwise, it demonstrates that the province has enough carbon emission right. The results of carbon emission permits of each province in 2016 are shown in Figure 4.

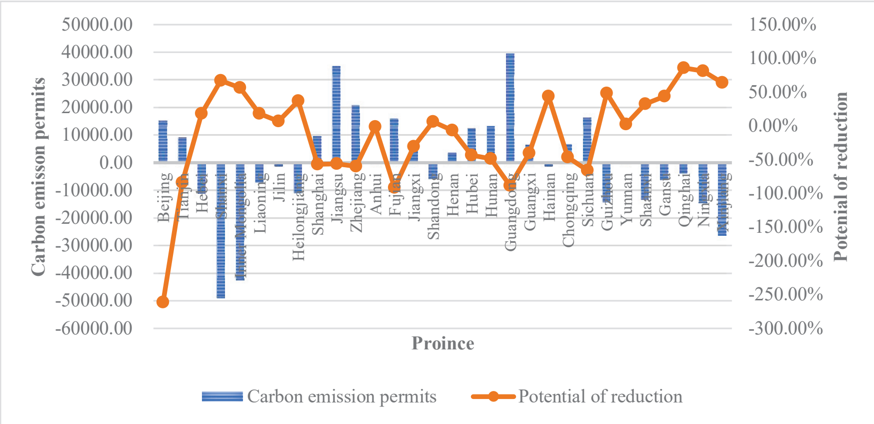

Figure 4. Carbon emission permits and emission reduction potential of provinces in 2016.

As shown in Figure 4, provinces with negative carbon emission permit value included Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Hainan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, and Xinjiang. In particular, some provinces located in the northern and western regions such as Shanxi, Inner Mongolia, Guizhou, Shaanxi, Ningxia, and Xinjiang had large negative corresponding values.

In order to compare the carbon emission permits of each region horizontally, this paper calculated the average space of carbon emission in six regions from 2007–2016, and the results are displayed in Figure 5.

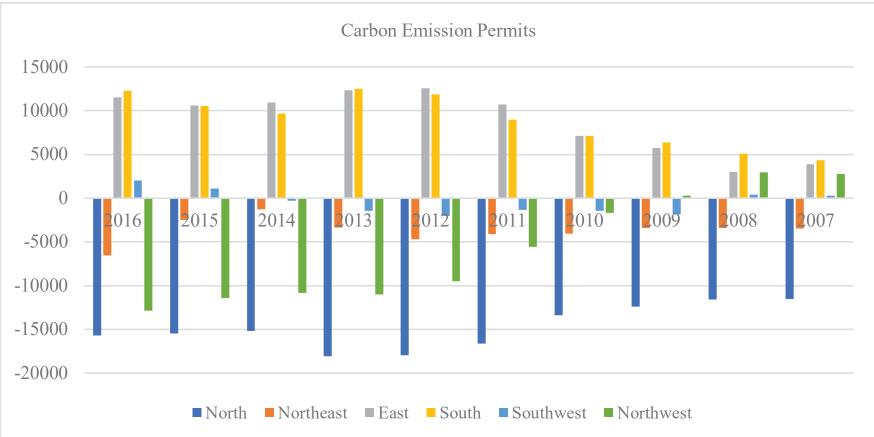

Figure 5. Carbon emission space of each region.

In Figure 5, the values of carbon emission permits in north and northeast China were negative from 2007–2016, and the phenomenon of excess emissions was most serious in 2011, 2012, and 2013. Although the situation has improved since 2014, it is still necessary to develop the production technology level and energy utilization to reduce CO_2 emissions. As for the northwest, carbon emission permit values continued to be negative after 2010. In addition, the carbon emission permits of the southwest were almost zero, which indicates that there was almost no difference between the actual consumption and carbon emissions. The space of carbon emission in southern and eastern areas was not only large, but also gradually increasing because of the economy and technology.

The indicator of carbon emission reduction potential was used to measure the emission reduction potential of a region, which is calculated as 1-(allocation/actually emission). If the value is below zero, i.e., the carbon allocation is greater than the actual consumption in the province, which indicates that there is no emission reduction potential, on the contrary, the province has a large potential of emission reduction. The carbon emission reduction potential of provinces in 2016 is shown in Figure 4.

As can be seen from Figure 4, the northeast and northwest regions, especially Shanxi, Inner Mongolia, Qinghai, Ningxia, and Xinjiang provinces, have huge potential for emission reduction, while there are few in the eastern and southern regions. In order to compare the carbon emission reduction potential of each region over time, we calculated the average potential of carbon emission reduction of the six regions from 2007–2016, and the results are shown in Figure 6 below.

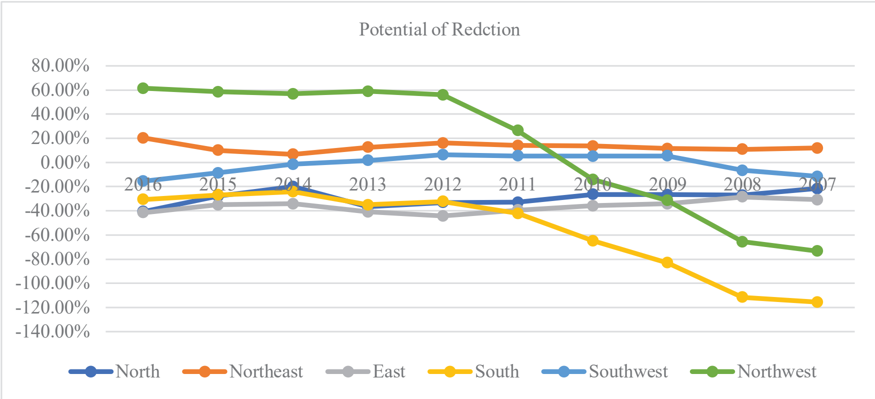

Figure 6. Carbon emission reduction potential of each region.

In Figure 6, the potential of carbon emission reduction in the north, northeast, southwest, and east was basically stable from 2007–2016. Furthermore, the carbon emission reduction potential of the northeast and southwest remained less, while that of northern and eastern China was below zero. The potential in regions such as the south and the northwest changed greatly, and the trend was basically the same. In addition, the potential of carbon emission reduction in the northwest increased significantly and gradually became stable after 2012.

To investigate the relationship between the carbon emission permits and the initial efficiency value of provinces from 2007–2016, Figure 7 is drawn as follows.

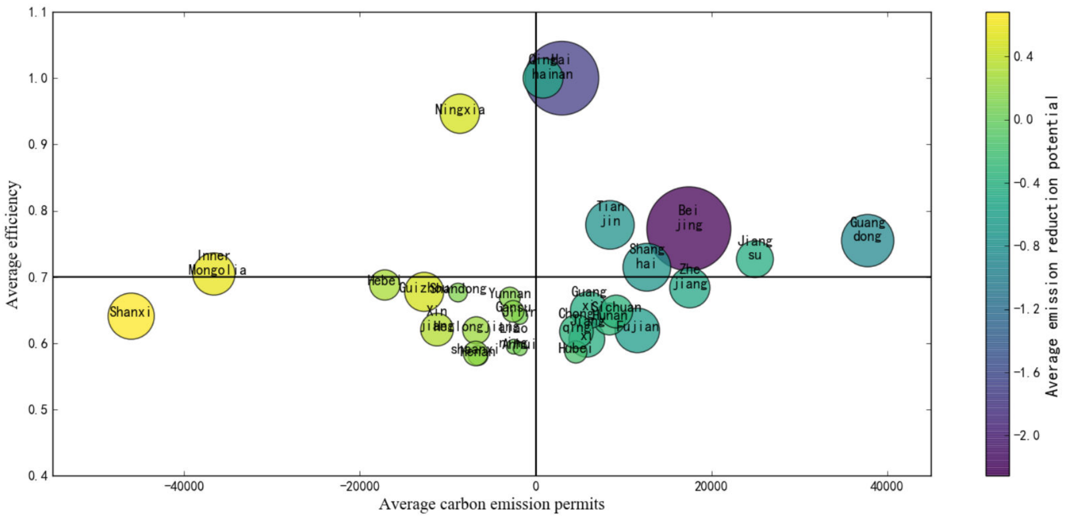

Figure 7. The average results of provinces.

The abscissa of Figure 7 represents the average space of carbon emission of each province from 2007–2016; the ordinate represents the average efficiency value of each province; and the color bar on the right represents the average potential of emission reduction. If the value of average emission reduction potential is below zero, then the color is dark, and the potential of emission reduction is less. As can be seen from Figure 7, 30 provinces were divided into four categories according to the average efficiency value (i.e., 0.7) and the space of carbon emission (i.e., zero). The provinces with an efficiency value greater than 0.7 and carbon emission permits greater than zero included Qinghai, Hainan, Beijing, Tianjin, Guangdong, Shanghai, and Jiangsu. The provinces with an efficiency value greater than 0.7 and the carbon emission permit less than zero included Ningxia and Inner Mongolia. The provinces with an efficiency value less than 0.7 and carbon emission space less than zero involved Shanxi, Hebei, Guizhou, Shandong, Yunnan, Gansu, Jilin, Xinjiang, Heilongjiang, Henan., and Shaanxi, while provinces with an efficiency value less than 0.7 and carbon emission permit greater than 0 were Liaoning, Anhui, Chongqing, Jiangxi, Hubei, Guangxi, Sichuan, Hunan, Fujian, and Zhejiang. Shanxi, Inner Mongolia, Ningxia, Guizhou, and other provinces have great potential for emission reduction. In addition, coastal areas had high efficiency values and carbon emission permits, but the efficiency value of the eastern, central, and southern regions were low, while northern regions had high efficiency values.

From Figure 8, Beijing and Hainan have no potential for emissions reduction, followed by Tianjin, Guangdong, Fujian, Shanghai, and other coastal regions. Additionally, some provinces such as Qinghai, Zhejiang, Guangxi, Jiangsu, Jiangxi, Hunan, Chongqing, Sichuan, and Hubei almost have no potential to reduce emissions, while Anhui, Liaoning, Jilin, Shandong, Henan, Yunnan, Shaanxi, Gansu, Hebei, and Heilongjiang have emissions reduction potential, and the potential of emission reduction in Xinjiang, Ningxia, Guizhou, Inner Mongolia, and Shanxi is the largest.

Figure 8. The average potential of emission reduction.

3.3. Policy Suggestions

Based on the above analysis, we draw the following conclusions. Firstly, there was no space for carbon emission in the north, northeast, and northwest from 2007–2016, particularly in the north and northwest where the carbon emission space was seriously insufficient. In southern regions, the space for carbon emission always existed during this period. In addition, the carbon emission permits of southern and eastern regions were increasing year by year. The actual carbon emission in southwestern regions was equivalent to the carbon emission allocation right, i.e., the carbon emission space barely fluctuated during this decade. Secondly, the potential of carbon emission reduction of each region tended to be stable after 2014, and in the north and northwest, it fluctuated greatly from 2007–2016. Besides, the northwest region had the potential of emission reduction since 2010, while this also existed in the north region after 2014.

Based on the above conclusions, this paper puts forward some policy suggestions of energy saving and emission reduction in provinces of China under the background of a low-carbon economy.

First, we need to define the scope of key regions and evaluate their emission reduction potential. During 2007–2016, the emission reduction potential of provinces such as Shanxi, Inner Mongolia, Guizhou, Heilongjiang, Hebei, Ningxia, Xinjiang, Gansu, Shaanxi, Yunnan, and Henan was higher. Shandong, Jilin, Liaoning, and Anhui had a certain potential to reduce emissions, and the emission reduction potential of other developed areas such as Guangdong, Beijing, and Tianjin was very low. It is worth noting that Hainan and Qinghai had significantly increased their emission reduction potential in recent years, as well as Shanxi, Ningxia, Xinjiang, and other places have great potential for emission reduction. In order to achieve the goal of emission reduction, we should focus on these areas.

Second, we should adjust and optimize the industrial structure and promote the green development of industry. In terms of the northeast, we should focus on these key areas and optimize industrial layout. At the same time, the prohibited or restricted industries, production technology, and industrial catalogs should be clearly defined. We should revise and improve the entry conditions for high energy consumption, high pollution, and resource-oriented industries. In addition, we should accelerate adjusting the distribution of industries in different regions and relocate, transform, or upgrade the enterprises with much pollution. Besides, we should strictly control the industrial production capacity with large energy consumption and high pollution, thoroughly deal with the industrial pollution, and strengthen comprehensive treatment of enterprises with a large amount of pollution. In the end, we should expand the scale of green industries such as industries of energy conservation, environmental protection, clean production, and clean energy, and new energy sources also need to be developed.

Finally, we should accelerate energy restructuring and build a low-carbon energy system. Especially, we should pay attention to the northeast of China as the focus. The specific measures are as follows: We should optimize the energy structure and develop new energy sources to reduce the ratio of coal and other fossil energy sources in total consumption. Moreover, we should improve energy efficiency and accelerate the development of clean and new energy sources. As for some regions with more private cars such as the eastern and southern, we should promote the use of vehicles with new energy, for example the number of buses, taxis, private cars, and other vehicles with new energy and clean energy should be increased and updated. In addition, we should take measures such as economic compensation to restrict the use of old vehicles and supervise the excess emissions in key areas. With respect to the northwestern region, we should optimize the energy structure and accelerate the upgrading of rural areas from coal to electricity and from coal to natural gas. Besides, some new energy such as nuclear energy, wind energy, solar energy, and other new energy sources should be developed to replace fossil fuels in a safe and effective manner.

4. Conclusions

Under the background of advocating energy saving and emission reduction, how to allocate carbon emission rights has become a hot research topic among global scholars. Especially in China, it is urgent to formulate a reasonable and effective scheme of carbon emission right allocation. In recent years, many researchers have applied DEA to the fixed cost allocation problem, among which carbon emission right allocation has become one of the most important applications, but all of this literature using traditional models considers each DMUs as a "black box" without taking the internal structure into account. However, it is more accurate for formulating the scheme when considering the inner operation of DMUs. This paper firstly adopts the two-stage DEA-network model to investigate the allocation plan of carbon emission right, and the algorithm in solving the unique allocation scheme is modified to make the result more accurate. Based on the result analysis, corresponding policy suggestions are given. First, we need to define the scope of key regions and evaluate their emission reduction potential. Second, we should adjust and optimize the industrial structure and promote the green development of industry. Finally, we should accelerate energy restructuring and build a low-carbon energy system.

Although it is reasonable for this paper to firstly apply the two-stage DEA network model to the research of carbon emission right allocation in China and the model established can be extended to other countries in the world, it has some limitations at the same time. On the one hand, for the treatment of undesirable output, we regard carbon emission as input; although policymakers hope the undesirable output to be as small as the input, this is actually inconsistent with the actual production process. On the other hand, this article does not consider the problems of the sharing of resources in the two stages and the addition of new inputs in the second stage, while the process of production is more realistic. Therefore, the above two points are our future research directions. Besides, the model adopted in this paper takes the size of the operational units into account to formulate a unique allocation plan, so it is also an improvement point to find a better method for dealing with the problem that allocation schemes are not unique.

Author Contributions: Conceptualization, X.J. and X.T.; methodology, X.J., B.Z., and X.T.; software, X.J.; validation, X.T. and K.R.; formal analysis, X.J.; investigation, X.J.; resources, X.J.; data curation, X.J.; writing, original draft preparation, X.J.; writing, review and editing, X.T. and C.W.; visualization, X.J.; supervision, B.Z. and X.T.; project administration, X.T.; funding acquisition, X.T.

Funding: This research was funded by the Natural Science Foundation of China Grant No. 61772011, the Open Project Foundation of Intelligent Information Processing Key Laboratory of Shanxi Province Grant No. CICIP2018002, the Social Science Foundation of Beijing Grant No. 16JDGLC005, the Project of Great Wall Scholar, Beijing Municipal Commission of Education, Grant No. CIT & TCD20170304 and No. CIT & TCD20180305, the Frontier Science Key Program of the Chinese Academy of Sciences Grant No. QYZDY-SSW-DQC004, the Beijing Municipal Science and Technology Project Grant No. Z171100004417025, and the Science and Technology Planning Project of Guangdong Province, China, Grant No. 2016B02024007.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Model (5) is a fractional model, so we need to transform it into a linear programming model by C-C transformation. Let $\tau = \frac{1}{\sum\limits_{i=1}^{m} v_i x_{id} + v_{m+1} R_{1d} + \sum\limits_{p=1}^{q} \varphi_p z_{pd} + v_{m+1} R_{2d}}$, $u_r = \tau \cdot \mu_r, \phi_p = \tau \cdot \varphi_p, v_i = \tau \cdot v_i, u_0 = \tau \cdot \mu_0, \phi_0 = \tau \cdot \varphi_0, v_{m+1} = \tau \cdot v_{m+1}$. Then, we have:

$$
\begin{aligned}
&\theta_d^{\star} = Max(\sum_{p=1}^{q} \phi_p z_{pd} + \phi_0 + \sum_{r=1}^{s} u_r y_{rd} + u_0) \\
&\text{s.t.} \quad \sum_{p=1}^{q} \phi_p z_{pj} + \phi_0 - \sum_{i=1}^{m} v_i x_{ij} - v_{m+1} R_{1j} \le 0, \quad \forall j = 1, 2, \ldots, n \\
&\sum_{r=1}^{s} u_r y_{rj} + u_0 - \sum_{p=1}^{q} \phi_p z_{pj} - v_{m+1} R_{2j} \le 0, \quad \forall j = 1, 2, \ldots, n \\
&\sum_{i=1}^{m} v_i x_{id} + v_{m+1} R_{1d} + \sum_{p=1}^{q} \phi_p z_{pd} + v_{m+1} R_{2d} = 1 \\
&\sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \ge 0, \quad \forall j = 1, 2, \ldots, n \\
&u_r, \phi_p, v_i \ge 0, v_{m+1} > 0, \quad \forall r = 1, \ldots, s; p = 1, \ldots, q; i = 1, \ldots, m
\end{aligned}
\tag{A1}
$$

Model (A1) is still nonlinear due to $v_{m+1} R_{1j}$ and $v_{m+1} R_{2j}$; in order to transform the model (A1) into a linear model, let $v_{m+1} R_{1j} = r_{1j}$, $v_{m+1} R_{2j} = r_{2j}$, then Model (A1) can be rewritten as Model (6).

Appendix B

Before calculating the operation size parameters, we use formula (A2) to normalize the original data.

$$\hat{x}_{ij} = \frac{x_{ij}}{\sum_{j=1}^{n} x_{ij}},\ \hat{z}_{pj} = \frac{z_{pj}}{\sum_{j=1}^{n} z_{pj}},\ \hat{y}_{rj} = \frac{y_{rj}}{\sum_{j=1}^{n} y_{rj}}, \quad \forall i, p, r, j \tag{A2}$$

Suppose the size parameters of the first stage and second stage are α_j and β_j, respectively. The size parameters are as follows:

$$\alpha_j = \frac{\sum\limits_{p=1}^{q} \hat{z}_{pj} \cdot \sum\limits_{i=1}^{m} \hat{x}_{ij}}{\sum\limits_{j=1}^{n} (\sum\limits_{p=1}^{q} \hat{z}_{pj} \cdot \sum\limits_{i=1}^{m} \hat{x}_{ij} + \sum\limits_{r=1}^{s} \hat{y}_{rj} \cdot \sum\limits_{p=1}^{q} \hat{z}_{pj})}, \quad \beta_j = \frac{\sum\limits_{r=1}^{s} \hat{y}_{rj} \cdot \sum\limits_{p=1}^{q} \hat{z}_{pj}}{\sum\limits_{j=1}^{n} (\sum\limits_{p=1}^{q} \hat{z}_{pj} \cdot \sum\limits_{i=1}^{m} \hat{x}_{ij} + \sum\limits_{r=1}^{s} \hat{y}_{rj} \cdot \sum\limits_{p=1}^{q} \hat{z}_{pj})} \tag{A3}$$

where $\sum\limits_{j=1}^{n} (\alpha_j + \beta_j) = 1$.

Appendix C

Since the model (8) is nonlinear, we need to do the following processing to change it into a linear model.

Let $|\alpha_j R - R_{1j}| + \alpha_j R - R_{1j} = 2c_{1j}$, $|\alpha_j R - R_{1j}| - \alpha_j R + R_{1j} = 2c_{2j}$, $|\beta_j R - R_{2j}| + \beta_j R - R_{2j} = 2d_{1j}$, $|\beta_j R - R_{2j}| - \beta_j R + R_{2j} = 2d_{2j}$, then the model (8) is transformed to Model (A4).

$$\begin{aligned}
& MinMax(c_{1k} + c_{2k} + d_{1k} + d_{2k}) \\
& \text{s.t.} \quad \alpha_j R - R_{1j} = c_{1j} + c_{2j} \quad \forall j = 1, 2, \ldots, n \\
& \beta_j R - R_{2j} = d_{1j} - d2j, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& c_{1j}, c_{2j}, d_{1j}, d_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& u_r, \phi_p, v_i \geq 0, \quad \forall r = 1, 2, \ldots, s; p = 1, 2, \ldots, q; i = 1, 2, \ldots, m
\end{aligned} \tag{A4}$$

Although the model (A4) is linear, it cannot be directly solved since this model involves multiple objectives. Therefore, we let $Max(c_{1k} + c_{2k} + d_{1k} + d_{2k}) = \rho$, then the model (A4) can be rewritten as the model (A5).

$$
\begin{aligned}
& MinMax \quad \rho \\
& \text{s.t.} \quad c_{1j} + c_{2j} + d_{1j} + d_{2j} - \rho_j = 0, \quad \forall j = 1, 2, \ldots, n \\
& \rho_j - \rho \leq 0, \quad \forall j = 1, 2, \ldots, n \\
& \alpha_j R - R_{1j} = c_{1j} + c_{2j} \quad \forall j = 1, 2, \ldots, n \\
& \beta_j R - R_{2j} = d_{1j} - d2j, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{p=1}^{q} \phi_p z_{pj} - \sum_{i=1}^{m} v_i x_{ij} - R_{1j} + \phi_0 = 0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{p=1}^{q} \phi_p z_{pj} - R_{2j} + u_0, \quad \forall j = 1, 2, \ldots, n \\
& \sum_{j=1}^{n} (R_{1j} + R_{2j}) = R, R_{1j}, R_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& c_{1j}, c_{2j}, d_{1j}, d_{2j} \geq 0, \quad \forall j = 1, 2, \ldots, n \\
& u_r, \phi_p, v_i \geq 0, \quad \forall r = 1, 2, \ldots, s; p = 1, 2, \ldots, q; i = 1, 2, \ldots, m
\end{aligned}
\tag{A5}
$$

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