Environ. Eng. Res. 2016; 21(1): 91-98
http://dx.doi.org/10.4491/eer.2015.107

pISSN 1226-1025
eISSN 2005-968X

Regional allocation of carbon emissions in China based on zero sum gains data envelopment analysis model

Lei Wen†, **Er nv Zhang**

Department of Economics and Management, North China Electric Power University, Hebei 071003, China

ABSTRACT

Along with China's increasing share in global total CO_2 emissions, there is a necessity for China to shoulder large emission-mitigating responsibility. The appropriate allocation of CO_2 emission quotas can build up a solid foundation for future emissions trading. In views of originality, an optimized approach to determine CO_2 emissions allocation efficiency based on the zero sum gains data envelopment analysis (ZSG-DEA) method is proposed. This paper uses a non-radial ZSG-DEA model to allocate CO_2 emissions between different Chinese provinces by 2020 and treats CO_2 as the undesirable output variable. Through the calculation of efficiency allocation amounts of provincial CO_2 emissions, all provinces are on the ZSG-DEA efficiency frontier. The allocation results indicate that the cumulative optimal amounts of CO_2 emissions in 2020 were higher than the actual amounts in 13 provinces, and lower in other 17 provinces, and show that different provinces have to shoulder different mitigation burdens in terms of emission reduction.

Keywords: Carbon emission allocation, CO_2 emissions, Data envelopment analysis, Zero sum gains

1. Introduction

There is a global consensus that climate change is being driven by an increase in atmospheric greenhouse gases, most notably CO_2 emissions. Along with the global climate and environment situation becoming more serious, as main element of greenhouse gas, CO_2 emissions are concerned.

To address this issue, Chinese government proposed targets that CO_2 emissions per unit gross domestic product (GDP) should be cut by 40-45% in 2020 compared to 2005. As a restriction index, this target has been included in the future medium-and-long term plans for national economic and social development. In order to achieve the goal of carbon emission reduction, the choice of carbon dioxide emissions allocation method and initial quotas confirmation must be solved as important topic of research.

Data envelopment analysis is effective for a non-parametric approach. It has been widely used in solving the problem of resource allocation. Moreover, DEA-relative models have been proposed in the presence of undesirable outputs especially CO_2 emissions. However, dated from the increasing CO_2 emissions, these models implied a reduction in performance. Thus, these existing models are not used to CO_2 emissions reallocation on account of the assumption of constant total sum. In this respect, ZSG-DEA model shows much more priority to deal with sum-constant reallocation problem, especially the interactive combination with Environment Production Technology. Consequently, ZSG environmental production technology allocation model is proposed to equitably and economically distribute CO_2 reduction responsibility among China's provinces. Particularly, the Chinese central government released a new regulation guiding the trade of carbon emission quotas in December 2014. This paper can help facilitate the implementation of this regulation by allocating the appropriate regional CO_2 emissions.

From an academic viewpoint, the allocation of CO_2 emissions has been widespread studied. Holmberg et al. [1] to allocate CO_2 emissions and fuel costs by using the energy, exergy and market. A system and quantitative method is proposed to implement the "common but differentiated responsibilities" rule of distribution of carbon dioxide emissions by Wei et al [2]. Pan et al. [3] emphasized "Equitable Access to Sustainable Development" for per capita cumulative CO_2 emission rights allocation schemes. Morini et al. [4] raised a method for the optimal demand allocation among combined heat and power (CHP) and renewable energy systems to minimize the primary energy consumption. Hasan et al. [5] presented a benefit-based allocation method by using a Shapley value approach. Wang

Received September 4, 2015 **Accepted** January 15, 2016

† Corresponding author
Email: 307353121@qq.com
Tel: +8615933987143

et al. allocated CO_2 emission quotas to major countries using different regimes for a sample period of 2011-2100 [6]. Levihn compared different allocation methods and discusses both advantages and disadvantages of each method [7]. There are a number of papers to use GDP to analyze irrigation future of agricultural water management in Africa [8-10].

Different from these previous studies, this paper attempts to employ DEA to allocate CO_2 emissions. As a non-parametric approach, DEA has been widely used in the resource allocation problem studied by Fang and Zhang [11]. especially the allocation problem with a fixed total amount of input or output. It is considered that Cook and Kress proposed the first model [12], under the DEA framework, that deals with the fixed input allocation problem. Cook and Kress's approach was based on output-oriented version of the CCR-DEA model, in which the objective of DEA model is to minimize the weighted combination of input variables with the constraint. Cook and Zhu extended this method to cases [13] that the input-oriented CCR-DEA model was utilized. Lin R. presented several DEA models to solve the same fixed input resources allocation problem [14]. Aparicio and Monge et al. also conducted research on such problems of the emission permits allocation [15]. In their study, a centralized point of view was adopted in DEA method to correspond to the three objectives: maximizing aggregated desirable production, minimizing the consumption of input resources, and minimizing undesirable total emissions.

By introducing the zero sum game concepts in to the DEA method, Gomes and Lins developed a ZSG-DEA model which was used to reallocate CO_2 emissions allowance among the Annex I parties and Non-Annex I countries of Kyoto Protocol. [16] Also by using ZSG-DEA model, Serrao proposed a model to efficiently reallocate agricultural greenhouse gas emissions among 15 EU countries [17]. Since the DEA based method has been successfully and effectively applied in the resource allocation problem, in this paper we choose a DEA based approach for the CO_2 emissions allowance allocation over the provinces in China.

One of the key issues related to the CO_2 emissions allowance allocation under the DEA framework is how to deal with the CO_2 should be be minimized. There are several approaches to modelling such types of undesirable outputs in the DEA context, for instance, dealing the undesirable outputs through a weak disposability reference technology by assuming the undesirable outputs and desirable outputs are generated in the same production process proposed by Färe et al and Arita Duasa et al [18-19]. Feng G, Färe et al and Lozano and Gutierrez applying the directional distance function to simultaneously increase the desirable outputs and decrease the undesirable outputs [20-22]. Cheng and Liu [23] translating the undesirable outputs into desirable outputs mathematically under the classification in variance and treating the undesirable outputs as inputs by Zhou et al and Zhang et al [24-25]. Furthermore, Sueyoshi et al and Goto proposed a DEA model using the range adjusted measure which combined the undesirable and desirable outputs in a unified treatment [26-28]. Since the regional CO_2 emissions allowance is a sub-divided quota of the total emission control target of China, which can essentially be considered as a distribution of the resource to each region, the approach proposed in this paper therefore realistically treats the undesirable outputs of the CO_2 emissions allowance as inputs.

2. Materials and Methods

2.1. CCR-DEA Model and Environmental ZSG-DEA

Assuming that there are *G* decision making units (DMUs) which convert *s* inputs into *t* outputs. Let x_{ig} denote the i-th input and y_{jg} denote the j-th output for DMUg. The classic output-oriented CCR model which was proposed by Charnes et al. [29] for calculating the technical efficiency of DMUg can be expressed in Eq. (1).

$$\begin{aligned} &\text{Max} \quad h_g \\ &s.t. \quad \sum_{g=1}^{G} \lambda_g x_{ig} \le x_{ig}, \quad i = 1, \cdots, s \\ &\sum_{g=1}^{G} \lambda_g y_{jg} \ge h_g y_{jg}, \quad j = 1, \cdots, t \\ &\lambda_g \ge 0, \quad g = 1, \cdots, G \end{aligned} \tag{1}$$

Once Eq. (1) is solved, the ZSG-DEA model can be constructed by using the efficiency scores derived from Eq. (1). The ZSG-DEA model was first proposed by Lins et al. [30] in order to estimate the winning efficiency of different countries in Olympics. The idea is that the total amount of an input (output) is fixed so that a decrease in the input (output) for one DMUcan lead to an increase in the input(output) for another DMUg. As discussed by Gomes and Lins [16], the output-oriented ZSG-DEA model can finally be formulated in Eq. (2).

$$\begin{aligned} &\text{Max} \quad h_{rg} \\ &h_{rg} y_{ig} \le \sum_p \lambda_p y_{ip} \left| 1 - \frac{y_{ip}(h_p - 1)}{\sum_{p \ne k} y_{ip}} \right| \\ &\sum_p \lambda_p x_{jp} \le x_{jg} \\ &\lambda_p \ge 0 \quad \text{for } \forall\ p \end{aligned} \tag{2}$$

Where hp represents expansion factor for DMUp that can be calculated from Eq. (1), and h_{rg} represents expansion factor of DMU_g evaluated by ZSG-DEA. The ZSG-DEA model has been widely used for the cases with single input or output variables in resource allocation.

In this paper, we constructed a ZSG-DEA model for CO_2 emission allocation based on the assumption that CO_2 emissions are weakly disposable. Similar to many previous studies such as Zhou et al. [31], we choose capital stock (*K*), population (*P*) and energy consumption (*E*) as three inputs, GDP (*Y*) as a single desirable output and CO_2 emissions (*C*) as a single undesirable output. Then the macro-production process can be modeled by the following Environmental Production Technology exhibiting constant returns to scale:

$$T=\{(E,K,P,Y,C): \sum_{k=1}^{k}\lambda_k E_k \le E$$
$$\sum_{k=1}^{k}\lambda_k K_k \le K$$
$$\sum_{k=1}^{k}\lambda_k P_k \le P$$
$$\sum_{k=1}^{k}\lambda_k Y_k \le Y$$
$$\sum_{k=1}^{k}\lambda_k C_k \le C$$
$$\lambda_k \ge 0, k=1,2,\cdots,k\} \tag{3}$$

The environmental production technology T, also referred to as environmental DEA technology, can satisfy both weak disposability and null-jointness assumptions. The weak disposability assumption indicates that it is possible to reduce CO_2 emissions and GDP proportionally, while the null-jointness assumption implies that removing all the CO_2 emissions must be at the cost of zero GDP. Based upon Eq. (3), we can easily formulate the following undesirable output orientation DEA model for calculating the CO_2 emission expansion coefficient. This study focuses on the CO_2 emission allocation and treats CO_2 emission as the undesirable output, the emission expansion coefficient is the technical efficiency in our model, which means a larger expansion coefficient reflects higher technical efficiency.

$$\text{Max} \quad h_p$$
$$\sum_{g=1}^{G}\lambda_g E_g \le E_p$$
$$\sum_{g=1}^{G}\lambda_g K_g \le K_p$$
$$\sum_{g=1}^{G}\lambda_g POP_g \le POP_p$$
$$\sum_{g=1}^{G}\lambda_g CO_{2g} \le h_p\, CO_{2p}$$
$$\sum_{g=1}^{G}\lambda_g GDP_g \le GDP_p$$
$$\lambda_g \ge 0,\ g=1,\cdots,G \tag{4}$$

With the consideration of research findings in Gomes et al. [16] and the basis of environmental DEA technology, this paper formulate the ZSG-DEA model in Eq. (5) the total amount of CO_2 emissions for all the DMUs is fixed. Provided that the CO_2 emissions for DMUg are decreased, the portion reduced by the DMU will be allocated to other DMUs, proportional to their actual amounts of CO_2 emissions.

$$\text{Max} \quad h_{rp}$$
$$h_{rp}\, CO_{2p}=\sum_{g=1}^{G}\lambda_g\, CO_{2g}\left|1-\frac{CO_{2p}(h_{rp}-1)}{\sum_{g\ne p} CO_{2g}}\right|$$
$$\sum_{g=1}^{G}\lambda_g E_g \le E_p$$
$$\sum_{g=1}^{G}\lambda_g K_g \le K_p$$
$$\sum_{g=1}^{G}\lambda_g POP_g \le POP_p$$
$$\sum_{g=1}^{G}\lambda_g GDP_g \le GDP_p$$
$$\lambda_g \ge 0, g=1,\cdots,G \tag{5}$$

Lins et al. [30] and Gomes and Lins [16] showed that there exists a relationship between h_p and the ZSG-DEA h_{rp}. Following Gomes and Lins, we derive the following Eq. (6) for solving h_{rp} from h_p:

$$h_{rp}=\left[1+\frac{\sum_{j\in W} CO_{2jp}(\theta_{nm}h_{rp}-1)}{\sum_{j\notin W} CO_{2jp}}\right] \tag{6}$$

where W represents the set of cooperative DMUs with hp higher than unity and $\theta_{nm}=h_n/h_m$. The DMUs belonging to W need to decrease their CO_2 emissions by $\sum_{j\in W} C_j(\theta_{nm}h_{rp}-1)$, which will be allocated to the DMUs that do not belong to W.

2.2. Grey Model

The grey system was proposed by Deng [32]. The grey system theory has been successfully applied in many fields such as management, economy, engineering, finance, etc. There are three types of systems-white, black, and grey. A system is called a white system when its information is totally clear. When a system's information is totally unknown, it is called a black system. If a system's information is partially known, then it is called a grey system. The grey forecasting model adopts the essential part of the grey system theory. The Grey Model GM (1,1) grey forecasting model can be used in circumstances with relatively little data, and it can use a first-order differential Eq. to characterize an unknown system. So the GM (1,1) grey forecasting model is suitable for forecasting the competitive environment where decision makers can reference only limited historical data. The GM (1,1) procedure can be separated into five steps:

Step 1: Collect original data and build a data sequence. The observed original data are defined as $X^{(0)}(i)$, where i is i th sample. The raw sequence of n samples is defined as:

$$X^{(0)}=(x^{(0)}(1),x^{(0)}(2),\cdots,x(0)(n)),\ x^{(0)}(k)>0,$$
$$k=1,2,\cdots,n. \tag{7}$$

Step 2: Transform the original data sequence into a new sequence. A new sequence $X^{(1)}$ generated by the accumulated generating operation (AGO), where

$$X^{(1)}=(x^{(1)}(1), x^{(1)}(2), \cdots, x^{(1)}(n)). \tag{8}$$

The $x^{(1)}(k)$ is derived as follows:

$$x^{(1)}(k)=\sum_{i=1}^{k} x^{(0)}(i), \quad k=1,2, \cdots, n. \tag{9}$$

Step 3: Build a first-order differential Eq. of the GM (1,1) model. By transforming the original data sequence into a first-order differential Eq., the time series can be approximated by an exponential function. The grey differential model is obtained as

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=b, \tag{10}$$

where a is a developing coefficient and b represents the grey input. According to Eqs. (8) and (10), the parameters a and b can be estimated by the least-squares method. Parameter $\hat{a}$ is represented as

$$\hat{a}=(B^TB)^{-1}B^TY, \tag{11}$$

Where

$$B=\begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \vdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix}, \; Z^{(1)}=(z^{(1)}(2), z^{(1)}(3), \cdots, z^{(1)}(n)). \tag{12}$$

The background value for formula (12) is represented as

$$z^{(1)}(k)=\frac{1}{2}(x^{(1)}(k)+x^{(1)}(k-1)), \quad k=2,3, \cdots, n \tag{13}$$

And

$$Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix} \tag{14}$$

Step 4: By substituting the estimated parameters obtained from Eqs. (11) to (14) into

Eq. (10), we get the grey forecasting predictor as follows:

$$\hat{x}^{(1)}(k+1)=\left(x^{(1)}(0)-\frac{b}{a}\right)e^{-ak}+\frac{b}{a}$$
$$\text{where } k=1,2, \cdots, n. \tag{15}$$

Step 5: Check the process: after a new sample is obtained, Steps 1 to 4 are followed to predict the behavior of the process until unusual conditions occur. If a new predicted point is plotted beyond the upper or lower limits, it means that the process may be out-of-control and that an investigation will be started; otherwise, the process continues to be monitored.

3. Results and Discussion

3.1. Variables and Data Description

We apply the ZSG-DEA model by using Eqs. (4)-(6) to investigate how to efficiently allocate China's CO_2 emissions to different provinces by 2020. All data covering the period of 2004–2012 were obtained from the Chinese Statistical Yearbook. Data on capital stock were obtained by using the perpetual inventory method described in Shan [33], while data on other variables came from various issues of China's Energy Statistics Yearbooks and China Statistical Yearbooks.

The data on CO_2 emissions at province level are not available. With reference to the 2006 IPCC National Greenhouse Gas Inventories, energy-related CO_2 emissions can be calculated as Eq. (16),

$$I=\sum_{i=1}^{4} E_i \times K_i \times \frac{44}{12} \tag{16}$$

where I denotes total CO_2 emissions, K_i is carbon emission coefficient of the kind of primary energy, E_i refers to the i_{th} kind of primary energy consumption, and 44/12 is ratio of molecular weights of CO_2 and C. Primary energy carbon emission coefficients are recommended by the *Energy Research Institute of Chinese National Development and Reform Commission*. Coefficients for coal, fossil oil, natural gas, and nonfossil energy are 0.7476, 0.5825, 0.4435 and 0 respectively (ton C/ton standard coal).

The prediction of China's economic growth, capital stock, population, energy consumption and CO_2 emissions by 2020 are given as follows.

First of all, according to the research of the *Development Research Center of the State Council of China* (Wang, 2005) [34] and the EIA (2009), annual GDP growth rate of China in 2011–2020 is 5.3% and 6.4% (in the low economic growth scenarios) and 7.4% and 8% (in the high economic growth scenarios) respectively. Here, annual GDP growth rate during 2010–2020 is assumed as 8%.

Secondly, according to the research of the United Nations Department of Economic and Social Affairs, China's population by 2020 will be 1.43 billion (UNDESA, 2009) [35]. We use this population projection.

Thirdly, according to the research of physical capital stock grow at average rate of 14% and 10. 96% of the depreciation in china during 2013-2020 proposed by Lin [36], China's capital stock by 2020 is calculated based on the perpetual inventory method and to adjust in 1952.

Furthermore, energy consumption forecasting model is a small sample data trend modeling problem. Grey forecasting model has a strong ability to deal with the information of small sample. We can directly use GM (1,1) model to predict for energy consumption in China during 2004-2012 and analysis error of historical actual data and predicted value.

Table 1. The Energy Consumption Prediction of China in 2004 - 2012

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
Actual value	231452.00	263458.00	290537.00	318974.00	337703.00	357238.00	389511.00	422745.00	443216.00
Predicted value	238441.85	272231.15	298526.77	328192.35	352460.62	370170.02	401819.55	433863.19	456689.77
Error (%)	3.02	3.33	2.75	2.89	4.37	3.62	3.16	2.63	3.04

Note: Unit:10^4 tons of standard coal

Table 2. The Error Rate of Carbon Dioxide Emissions for 30 Provinces in 2004 - 2012

Province	Error (%)	Province	Error (%)	Province	Error (%)
Beijing	3.33	Zhejiang	2.82	Hainan	10.1
Tianjin	3.94	Anhui	3.92	Chongqing	6.16
Hebei	3.94	Fujian	1.85	Si chuan	2.77
Shanxi	4.11	Jiangxi	3.96	Guizhou	3.77
Inner Mongolia	6.90	Shandong	6.56	Yunnan	5.88
Liaoning	1.61	Henan	6.57	Shannxi	2.44
Jilin	2.09	Hubei	2.89	Gansu	3.56
Heilongjiang	1.22	Hunan	4.97	Qinghai	3.95
Shanghai	2.11	Guangdong	2.13	Ningxia	6.92
Jiangsu	5.2	Guangxi	4.32	Xinjiang	2.17

Table 3. Descriptive Statistics of Input and Output Variables for 30 Provinces by 2020

Variable	Unit	Mean	Standard deviation	Minimum	Maximum
GDP	10^8 yuan	36191.95	26188.45	3636.84	107070.81
Capital stock	10^8 yuan	24230.91	20012.63	1207.03	73608.97
Population	10^4 persons	4706.73	2800.87	603.64	11116.18
Energy coconsumption	10^4 tce	27317.20	15476.39	3839.00	64084.00
CO_2 emission	10^6 tons	593.69	354.45	78.45	1450.99

As can be seen in Table 1, the error is below 5%. The forecasted results show that the method is feasible and the forecasted results well match the actual measured data. Thus, energy consumption of each province is calculated using the gray forecast in 2020.

Finally, we take 2004-2012 data of all provinces except Tibet as samples, using GM (1,1) model to forecast carbon dioxide emissions of 30 provinces in China in 2004-2012. By comparing the predicted results with real numerical values from Table 2, we can reach that the prediction of carbon dioxide emissions which uses the GM (1,1) model is credibility. Thus, the carbon dioxide emissions of 30 provinces by 2020 can be obtained.

Table 3 lists the descriptive statistical results of the five variables in China by 2020. Unfortunately, due to the lack of data, Tibet, Hong Kong, Macau and Taiwan were not included in this study, while other 30 provinces, autonomous regions and provincial municipalities (such as Beijing, Shanghai, Tianjin and Chongqing) were included.

3.2. Empirical Results

We first calculate the CO_2 emission h_p scores by using Eq. (4), which is listed in Table 4. It is clear that in 2020 several less developed provinces, e.g. Hebei, Shanxi, Inner Mongolia, Liaoning and Ningxia had h_p score of unity, indicating that the amounts of CO_2 emissions in these provinces were too large to be further expanded. On the contrary, their CO_2 emissions need to be reduced in order to keep consistency with their current input and output levels. Table 4 also lists that some provinces or provincial leveled municipalities (such as Beijing and Hainan) had larger h_p scores, which could be explained by their higher CO_2 emission efficiency. Most of the province's expansion coefficient is 1, which means that the level of carbon emissions in most of the provinces in China is relatively high. We need to pay attention to it in the future development process and improve at the harmonious development of the energy, economic and social development.

We further apply the ZSG-DEA model to derive the ZSG-DEA h_{rp} scores by using Eq. (6) and the optimal amounts of CO_2 emissions foreach province. Table 5 lists the results for the year 2020, which suggests that provinces with h_{rp} higher than 1 can be allowed increasing their CO_2 emissions so as to reach ZSG-DEA frontier. For example, in 2020 Beijing could be allowed increasing CO_2 emissions by 24.13 million tons. On the other hand, those provinces with h_{rp} lower than unity should reduce their CO_2 emissions in order to reach ZSG-DEA frontier. For instance, Hebei province had to reduce 35.85 million tons of CO_2 emissions. Based on the previous analysis we find that when total amount of CO_2 emission in China remains no changes, all the provinces become more efficient after appropriate reallocation.

We also present our CO_2 emission allocation results in different regions in Fig. 1, showing that the comparison between the results of the ZSG-CO_2 emission and Initial CO_2 emission in 2020. There are 13 provinces in the allocation of ZSG exceeded the actual amount of emissions, while other 17 provinces of ZSG allocation

Table 4. CO_2 Emission Coefficient of Expansion in China by 2020

Province	h_p	Province	h_p	Province	h_p
Beijing	1.187	Zhejiang	1.034	Hainan	1.268
Tianjin	1.007	Anhui	1.000	Chongqing	1.049
Hebei	1.000	Fujian	1.000	Si chuan	1.080
Shanxi	1.000	Jiangxi	1.000	Guizhou	1.000
Inner Mongolia	1.000	Shandong	1.047	Yunnan	1.000
Liaoning	1.000	Henan	1.009	Shanxi	1.081
Jilin	1.056	Hubei	1.000	Gansu	1.090
Heilongjiang	1.074	Hunan	1.000	Qinghai	1.135
Shanghai	1.000	Guangdong	1.045	Ningxia	1.000
Jiangsu	1.000	Guangxi	1.000	Xinjiang	1.153

Table 5. ZSG Coefficient of Expansion and ZSG-CO_2 Emission in China by 2020

Province	Initial CO_2 emission (million tce)	h_{rp}	ZSG-CO_2 emission (million tce)	Adjustment
Beijing	157.58	1.153	181.71	24.13
Tianjin	284.75	0.978	278.57	-6.18
Hebei	1257.18	0.971	1221.33	-35.85
Shanxi	901.63	0.971	875.92	-25.71
Inner Mongolia	1162.69	0.971	1129.54	-33.15
Liaoning	990.06	0.971	961.83	-28.23
Jilin	432.4	1.026	443.59	11.19
Heilongjiang	480.73	1.043	501.58	20.85
Shanghai	337.06	0.971	327.45	-9.61
Jiangsu	1044.92	0.971	1015.12	-29.80
Zhejiang	566.45	1.005	569.01	2.56
Anhui	507.12	0.971	492.66	-14.46
Fujian	406.68	0.971	395.08	-11.60
Jiangxi	308.57	0.971	299.77	-8.80
Shandong	1450.99	1.017	1475.87	24.88
Henan	1044.92	0.980	1024.26	-20.66
Hubei	761.97	0.971	740.24	-21.73
Hunan	459.96	0.971	446.84	-13.12
Guangdong	1004.51	1.015	1019.78	15.27
Guangxi	423.27	0.971	411.20	-12.07
Hainan	112.21	1.232	138.23	26.02
Chongqing	318.04	1.019	324.11	6.07
Sichuan	552.29	1.049	579.46	27.17
Guizhou	361.98	0.971	351.66	-10.32
Yunnan	385.56	0.971	374.57	-10.99
Shanxi	726.69	1.050	763.15	36.46
Gansu	315.21	1.059	333.78	18.57
Qinghai	78.45	1.103	86.50	8.05
Ningxia	311.36	0.971	302.48	-8.88
Xinjiang	665.41	1.120	745.34	79.93
Total	17810.64	-	17810.64	0.00

amount is less than the actual emissions. In the 13 provinces, Guangdong, Sichuan and Chongqing have been promoted and made large utilization of hydropower, nuclear power and other clean energy. While Heilongjiang, Qinghai and Xinjiang are major agricultural provinces, the other 17 provinces are mostly based on industry. This phenomenon shows a high instability and uncertainty in the future.

From the perspective of economics analysis, some provinces are facing higher pressures on CO_2 emission reduction. If reducing CO_2 emissions only from the perspective of reducing energy consumption blindly, economic development and people's living fields are inevitably deteriorated. It is not rational to limit their energy

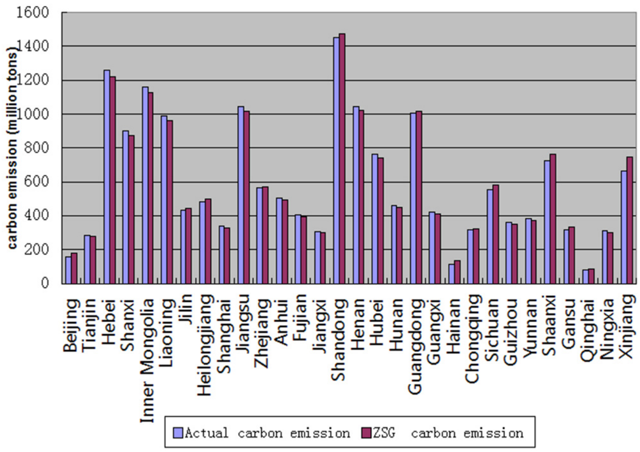

Fig. 1. Adjustment process of regional CO_2 emissions allowance.

consumption or even cut energy supply to the general public in order to achieve the national emission reduction targets. Therefore, efforts should focus on how to optimize local energy structure and promote energy saving in the whole societies, especially in the local industries. Renewable or cleaner energy sources, such as natural gas, wind power, solar power, and geothermal power, should be fully supported by considering the local energy endowments. Also, innovative efforts, such as eco design, energy audits, cleaner production, and industrial symbiosis, should be initiated especially in the local industries. In addition, economic instruments, such as carbon trading, carbon tax, carbon cap, should be applied so that provinces with more reduction potentials have adequate drivers to facilitate their carbon reduction efforts, while funds can be collected for supporting related research & development activities.

4. Conclusions

Along with China's status of being the greatest energy consumer and CO_2 emitter in the world, there is a huge necessity for China to achieve emission-cutting target through regional allocation of emission allowance equally. This paper developed a non-radial DEA model to measure CO_2 emissions to measure technical efficiency (the CO_2 emission expansion coefficient). The definition of technical efficiency was introduced in the methodology section. We calculate the technical efficiency through Eq. (4) and construct efficient allocation mechanism through Eqs. (5) and (6). After the ZSG allocation, every DMU's CO_2 emission is on the ZSG frontier, indicating the overall "Pareto Optimality". We treat CO_2 emission as one undesirable output to modify previous method in which CO_2 emissions are treated as the input variable.

After that, we employ empirical analysis to quantify the efficient allocation of CO_2 emissions between different provinces using China's provincial data for a sample in 2020. Our results show that the actual CO_2 emissions in some provinces (especially those energy-abundant provinces) were higher than their maximal CO_2 emission allowances calculated from the ZSG-DEA model, indicating that these provinces are facing great pressures on CO_2 emission reduction. Our results have a certain strategic significance for policy making. The level of ZSG-CO_2 emissions may be used as an indicator for monitoring the harmony between CO_2 emissions and other factors such as capital investment and economic development.

The inconsistency between ZSG-CO_2 emissions and the actual CO_2 emissions in different regions shows that regions react quite differently to this "dilemma" problem (to achieve both economic development and energy conservation and emission reduction). In order to achieve the proposed national emission reduction targets, different regions should collaborate through innovative efforts, such as the use of effective economic instruments, capacity building and technology transfer.

The conclusion drawn by this study is important for the government to adopt relative strategies and enrich the low-carbon-economy system in China. However, the research is still preliminary and worthy of further study, such as method improvement, in-depth analysis of variable relationship.

Acknowledgments

This work is supported by the Fundamental Research Funds for the Central Universities (No. 12ZX12).

References

1. Holmberg H, Tuomaala M, Haikonen T, Ahtila P. Allocation of fuel costs and CO_2 -emissions to heat and power in an industrial CHP plant: Case integrated pulp and paper mill. *Appl. Energ.* 2012;93:614-623.
2. Wei YM, Wang L, Liao H, Wang K, Murty T, Yan J. Responsibility accounting in carbon allocation: a global perspective. *Appl. Energ.* 2015;130:122-133.
3. Pan X, Teng F, Wang G. Sharing emission space at an equitable basis: allocation scheme based on the equal cumulative emission per capita principle. *Appl. Energ.* 2014;113: 1810-1818.
4. Morini M, Pinelli M, Spina PR, Venturini M. Optimal allocation of thermal, electric and cooling loads among generation technologies in household applications. *Appl. Energ.* 2013;112:205-214.
5. Hasan KN, Saha TK, Chattopadhyay D, Eghbal M. Benefit-based expansion cost allocation for large scale remote renewable power integration into the Australian grid. *Appl. Energ.* 2014;113: 836-847.
6. Wang LN, Ma D, Chen WY. Future CO_2 emissions allowances and inequality assessment under different allocation regimes. *Energy Procedia* 2014;61:523-526.
7. Levihn, F. CO_2 emissions accounting: Whether, how, and when different allocation methods should be used. *Energy* 2014;68: 811-818.
8. Valipour M. A comprehensive study on irrigation management in Asia and Oceania. *Arch. Agron. Soil. Sci.* 2015;61:1247-1271.
9. Valipour M, Ahmadi MZ, Raeini-Sarjaz M, et al. Agricultural water management in the world during past half century. *Arch. Agron. Soil. Sci.* 2014;61:1-22.

10. Valipour M, Valipour M. Future of the area equipped for irrigation. *Arch. Agron. Soil. Sci.* 2014;60:1641-1660.
11. Fang L, Zhang CQ. Resource Allocation Based on the DEA Model. *J. Oper. Res. Soc.* 2008;59:1136-1141.
12. Cook WD, Kress M. Characterizing an equitable allocation of shared costs: A DEA approach. *Eur. J. Oper. Res.* 1999;119:652-661.
13. Cook WD, Zhu J. Allocation of shared costs among decision making units: A DEA approach. *Comput. Oper. Res.* 2005;32:2 171-2178.
14. Lin R. Allocating fixed costs or resources and setting targets via data envelopment analysis. *Appl. Math. Comput.* 2011;217: 6349-6358.
15. Aparicio J, Monge JF, Pastor JT. New centralized resource allocation DEA models under constant returns to scale. *Boletín de Estadística e Investigación Operativa* 2012;28:110-130.
16. Gomes EG, Lins MPE. Modelling undesirable outputs with zero sum gains data envelopment analysis models. *J. Oper. Res. Soc.* 2008;59:616-623.
17. Serrao A. Reallocating agricultural greenhouse gas emission in EU 15 countries. In: Proceeding of the Agricultural & Applied Economics Association; 2010.
18. Färe R, Grosskopf S, Lovell CAK, Pasurka C. Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *Rev. Econ. Stat.* 1989;71:90-98.
19. Arita Duasa, Rafia Afroz. Modeling environmental performance and economic development. *IJTEF.* 2013:384-387.
20. Feng G, Serletis A. Undesirable outputs and a primal Divisia productivity index based on the directional output distance function. *J. Econometrics* 2014;183:135-146.
21. Färe R, Grosskopf S, Pasurka CA. Environmental production functions and environmental directional distance functions. *Energy* 2007;32:1055-1066.
22. Lozano S, Gutierrez E. Non-parametric frontier approach to modelling the relationships among population, GDP, energy consumption and CO_2 emissions. *Ecol. Econ.* 2008;66:687-699.
23. Cheng L, Liu J. Modeling undesirable factors in the measurement of energy efficiency in China. In: Management and Service Science, 2009 (MASS 09). International Conference on; 2009. p. 1-4.
24. Zhou Z, Liu W. DEA models with undesirable inputs, intermediates, and outputs. *Data Envelopment Analysis Springer US* 2015;415-446.
25. Zhang B, Bi J, Fan Z, Yuan Z, Ge J. Eco-efficiency analysis of industrial system in China: A data envelopment analysis approach. *Ecol. Econ.* 2008;68:306-316.
26. Sueyoshi T, Goto M, Ueno T. Performance analysis of US coal-fired power plants by measuring three DEA efficiencies. *Energ. Policy* 2010;38:1675-1688.
27. Sueyoshi T, Goto M. DEA approach for unified efficiency measurement: Assessment of Japanese fossil fuel power generation. *Energ. Econ.* 2011;33:292-303.
28. Sueyoshi T, Goto M. Environmental assessment by DEA radial measurement: U.S. coal-fired power plants in ISO (Independent System Operator) and RTO (Regional Transmission Organization). *Energ. Econ.* 2012;34:663-676.
29. Charnes A, Cooper WW, Rhodes E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* 1978;2:429-444.
30. Lins MPE, Gomes EG, Soares DM. Olympic ranking based on a zero sum gains DEA model. *Eur. J. Oper. Res.* 2003;148: 312-322.
31. Zhou P, Ang BW, Han JY. Total factor carbon emission performance: A Malmquist index analysis. *Energ. Econ.* 2010;32: 194-201.
32. Deng JL. Control problems of grey systems. *Syst. & Contr. Lett.* 1982;5:288-294.
33. Shan HJ. Re-estimating the capital stock of China: 1952-2006. *J. Quant. Tech. Econ.* 2008;10:17-32 [in Chinese].
34. Wang MK. Key issue in China's development (2006-2020). China Development Press: Beijing; 2005.
35. UNDESA. World population prospects: The 2008 revision. United Nations: New York; 2009.
36. Lin BQ, Sun CW. How can China achieve its carbon emission reduction target while sustaining economic growth? *Chinese Social Science Press* 2011.