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Study on the Efficiency of Carbon Quota Allocation in China's Provincial Thermal Power Industry

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Abstract*:* Based on data from 2010-2019, this paper uses an improved grey prediction model to forecast data on thermal power generation, energy consumption, installed thermal power capacity and the number of employees in the thermal power industry in each province of China in 2030, and conducts an evaluation study on the efficiency of carbon quota allocation in the thermal power industry in China in 2030. The results show that: 1) There is a large gap in the efficiency of carbon quota allocation between different provinces in China, and the analysis by dividing the provinces into regions shows that the reasons for this gap may be related to the different geographical locations, uneven economic development and inconsistent technological levels of each province. 2) The reallocation of carbon quotas through the ZSG-DEA model can effectively improve the carbon quota allocation efficiency of inefficient provinces. efficiency.3) The 16 provinces located in the economically less developed central and western regions of China with relatively low efficiency in carbon quota allocation, such as Hebei and Anhui, need to reduce their carbon quotas when allocating efficiently through the ZSG-DEA model, while the 14 provinces with relatively more developed economies and high efficiency in carbon quota allocation, such as Guangdong and Shandong, should increase their carbon quotas.

Keywords: Thermal Power Sector, Carbon Quotas, Grey Forecasting Models, ZSG-DEA

INTRODUCTION

The International Energy Agency (IEA) released its Global Energy and CO2 Status Report 2018 in March 2019, which states that energy-related carbon emissions increased by 1.7% globally in 2018, with the most notable increase being in coal-fired as well as gas-fired thermal power plants, which increased by 2.5% year-on-year, and coal-fired thermal power plants, which increased even more, by 2.9%. It was also the single largest contributor to the increase in carbon emissions. Thanks to its abundant coal reserves, China still relies on thermal power for the majority of its electricity generation in this day and age. According to available data, China's total installed thermal power capacity reaches 1.25 billion kilowatts in 2020, accounting for 56.8% of the country's total installed capacity, and coal-fired units alone account for 86.4% of all thermal power units, which is a significant contributor to the large amount of CO2 emissions from the thermal power sector! Despite the restricted development of many industries in 2020 due to the epidemic, overall, China's total CO2 emissions increase by 0.71% in 2020, with an increase of 0.7 billion tonnes to a total of 9.9 billion tonnes. As thermal power supply allows for stable supply, regulation of peaks and centralised heating, and plays an indispensable role in balancing the price of electricity, thermal power still accounts for more than 60% of China's total electricity generation, resulting in significant CO2 emissions, despite the Chinese government's intensified development of new energy sources in recent years (e.g. solar, nuclear and wind). The reduction of CO2 emissions from the thermal power sector, which is now one of the largest producers of CO2 in China, should be considered a priority in the fight against climate change [Meng, et. al., 2016].

Various extensions of the basic DEA model have also been developed for resource allocation. Beasley (2003) introduced a new DEA model designed to maximise the average efficiency of decision making units (DMUs) to incorporate organisational resource constraints. lins et al. (2003) first put forward the ZSG-DEA model, the main idea of which is "zero-sum game", i.e., a decrease in the number of one party must cause an increase in the number of the other party, and the main use of the model is to reallocate a certain indicator among the decision units to increase the value of efficiency. Since then, the ZSG-DEA model has been widely used for the study of efficiency allocation due to its ability to achieve optimal efficiency and Pareto optimality.

Gomes and Lins (2008) applied ZSG-DEA to carbon trading by arguing that for the same level of emissions, the party with higher population, energy consumption and GDP would be more efficient, and therefore considered emissions as an input variable . Following these developments, Wang et al. (2013) used a similar approach to examine not only the distribution of CO2 but also the distribution of energy between Chinese provinces in 2020. At the sectoral level, Zhang and Hao (2017) used the ZSG-DEA approach to study the efficiency of CO2 allocation in China in 2020. Furthermore, in addition, Cai and Ye (2019) analysed the impact of industrial structure on carbon emissions on top of the regional carbon emission allocation in 2020 using the ZSG-DEA model.

METHODOLOGY AND DATA

Improved grey prediction model

In this paper, a non-linear grey Bernoulli model is chosen to predict the data and a particle swarm optimisation algorithm is used to find the best of the Bernoulli parameters. The main process of the grey Bernoulli prediction model consists of the following steps:

1) Cumulative generation processing of the original data series.

Cumulative generation is to generate a new series by adding up the original data series. The cumulative generation process can increase the smoothness of the series and reduce the impact of the volatility of the original data series on the prediction accuracy. It is assumed that the time series data of the original data for the grey Bernoulli prediction model are

$$x^{(0)} = [x^{(0)}(1), x^{(0)}(2), x^{(0)}(3), ..., x^{(0)}(n)]$$

The first-order cumulative generation is then performed by the following equation to obtain the first-order cumulative generation sequence, called the 1-AGO sequence.

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i)$$

$k = 1,2,3,..,n$, the 1-AGO sequence is obtained as follows.：

$$x^{(1)} = [x^{(1)}(1), x^{(1)}(2), x^{(1)}(3),..., x^{(1)}(n)]$$

2）Constructing Bernoulli's differential equations and solving them

The first-order cumulative generating series obtained by 1-AGO cumulative generation is to some extent similar to the exponential series, which can be solved by the first-order differential equation, so the grey differential equation is constructed as follows.

$$\frac{dx^{(1)}}{dt} + ax^{(1)} = b[x^{(1)}]^r$$

3）Differentiation treatment equation：

$$\frac{\Delta x^{(1)}}{\Delta t} = \frac{x^{(1)}(k+1) - x^{(1)}(k)}{k+1-k} = x^{(1)}(k+1) - x^{(1)}(k) = x^{(1)}(k)$$

The neighbourhood mean of $X^{(1)}$ is：

$$z^{(1)}(k) = \alpha x^{(1)}(k) + (1-\alpha)x^{(1)}(k-1)$$

InGM(1,1) model，α =0.5，Bringing in the grey differential equation, we get：

$$x^{(0)}(k) + az^{(1)}(k) = b[z^{(1)}(k)]^r$$

4）Solving for coefficient vectors

Assume that the matrices B and Y：

$$B = \begin{bmatrix} -z^{(1)}(2) & [z^{(1)}(2)]^r \\ -z^{(1)}(3) & [z^{(1)}(3)]^r \\ \vdots & \vdots \\ -z^{(1)}(n) & [z^{(1)}(n)]^r \end{bmatrix}$$

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

Therefore, the parameter matrix of the grey Bernoulli prediction model can be derived by the least squares method as

$$[a, b]^T = [B^T B]^{-1} B^T Y$$

5）Constructing a time response function and calculating predicted values

The time response function can be derived by bringing the parameter matrix into the grey differential equation：

$$x^{(1)}(k) = \left[[[x^{(1)}(1)]^{(1-r)} - \frac{b}{a}]e^{-a(1-r)(k-1)} + \frac{b}{a} \right]^{-\frac{1}{1-r}}$$

A cumulative reduction of the forecast results leads to the final forecast.

$$\hat{x}^{(0)}(k) = \begin{cases} \hat{x}^{(0)}(1), (k = 1) \\ \hat{x}^{(1)}(k) - \hat{x}^{(1)}(k-1), (k = 2,3,...,n) \end{cases}$$

ZSG-DEAmodel

Assuming that an evaluation system has N decision making units (DMUs) of the same type, each with R input indicators and M output indicators, the BCC model for evaluating the relative efficiency of decision making unit DMU 0 using the DEA method is as follows.

$$\min\theta_0$$

$$\begin{cases} \sum_{i=1}^{30} \lambda_i y_{ij} \ge y_{0j} \ (j = 1, 2, 3) \\ \sum_{i=1}^{30} \lambda_i = 1 \\ \sum_{i=1}^{30} \lambda_1 x_{ik} \le \theta_0 x_{0k} \ (k = 1) \\ \lambda_i > 0 \end{cases}$$

Again using the example of input orientation, when a decision unit is not an efficient decision unit, it is assumed to have an efficiency value of δ_0. In order to achieve a higher efficiency value, it requires a reduction in the input variables, the specific reduction being

$$v = x_0 - \delta_0 x_0$$

The amount of CO2 received by the i-th decision unit from the target decision unit is

$$\frac{x_i}{\sum_{i\neq 0} x_i} \times x_0(1-\delta_0)$$

Since all decision units are undergoing proportional reduction of inputs, the final input (CO2 emissions) is redistributed to decision unit i as

$$\sum_{i\neq 0}\left[\frac{x_i}{\Sigma_{i\neq 0} x_i} \times x_0(1-\delta_0)\right] - x_i(1-\delta_0)$$

The input-oriented BCC model for the relative efficiency evaluation of decision unit DMU0 using the ZSG-DEA method according to the proportional abatement strategy is shown below.

$$\min \delta_0$$

$$\begin{cases} \sum_{i=1}^{30} \lambda_i y_{ij} \geq y_{0j}\ (j=1,2,3) \\ \sum_{i=1}^{30} \lambda_i = 1 \\ \sum_{i=1}^{30} \lambda_i x_i \left[1 + \frac{x_0(1-\delta_0)}{\sum_{i\neq 0} x_i}\right] \leq \theta_0 x_{0k} \\ \lambda_i > 0 \end{cases}$$

Selection of indicators for the ZSG-DEA model

Taking into account the interaction between the indicators in production activities and the availability of data, the system of indicators for the efficiency of carbon quota allocation is constructed from the following aspects.

(1) Non-energy inputs. The number of employees and installed thermal power capacity were selected as non-energy inputs. As China's statistics do not have a separate number of employees in the thermal power industry, data on the "electricity, heat, gas and water production and supply industry", which is highly relevant, were selected from the China Labour Statistics Yearbook 2020. The data on installed thermal power capacity is taken from the China Electricity Statistical Yearbook, "Installed Power Generation Capacity by Region (Thermal Power)" sub-table.

(2) Energy input. The energy consumption of thermal power generation was selected as the energy input. The energy consumption data in the "Thermal power generation" column of the regional energy balance sheet in the 2011-2020 China Energy Statistics Yearbook was selected, and the energy consumption was converted into standard coal consumption according to the discount factor.

(3) Expected output. Thermal power generation was selected as the desired output. Data from the table "Thermal power generation by region" in the China Energy Statistics Yearbook 2011-2020 were used.

Determination of initial carbon quota and target data for 2030

In the last 10 years, China's 13th and 14th Five-Year Plans have both mentioned the target of reducing the CO2 emission rate per unit of GDP, which are emissions per unit of GDP in 2025 will be 18% lower than in 2020, and CO2 emissions per unit of GDP in 2020 will be 18% lower than in 2015. In view of this, this paper also assumes an 18% reduction in CO2 emissions per unit of GDP in 2030 compared to 2025.

Since the current data is only available until 2019, the data for 2019 is used as the basis for the projections. Here we make two assumptions, the first: assume that the rate of change in CO2 emissions per unit of GDP is the same for each year, and the second: assume that carbon emissions from the thermal power sector account for the same proportion of total national carbon emissions in 2019 and 2030, so the formula for calculating carbon allowances in 2030 is

$$C = \frac{C_{2019}}{GDP_{2019}} \times 82\%^{\frac{11}{5}} \times GDP_{2030}$$

The growth rate of China's GDP has slowed down in recent years, and during the 13th Five-Year Plan period, the main feature of China's economic development is that the growth rate should shift from high to medium to high speed, with a GDP growth rate of 5.95% in 2019, 2.3% in 2020 due to the epidemic, and 8.1% in 2021. Combined with the current trend of declining GDP growth in China, this paper assumes an average GDP growth rate of 5% during the 14th Five-Year Plan period. It is further assumed that China's GDP will grow at an average rate of 4% during the 15th Five-Year Plan period.

The above assumptions are made because: under the "3060" dual carbon target, China's total carbon emissions will peak in 2030, and under the target of an 18% reduction in CO2 emissions per unit of GDP every five years, carbon emissions will only cease to increase when the five-year average GDP growth rate is 4.0488%. This means that we will only be able to achieve the 'peak carbon' target by 2030 if the five-year average GDP growth rate is less than 4.0488%. Therefore, assuming a GDP growth rate of 4% is easy to calculate and is essentially the fastest rate of growth within these limits.

The calculated carbon emissions in 2030 will be 5.68% higher than in 2019. This gives a total of 453,234,400 tons of carbon allowances for the thermal power sector in China in 2030.

Using the improved grey forecasting model mentioned above to forecast input-output data, the final data on installed thermal power capacity, energy consumption, employment and thermal power generation in China's thermal power industry in 2030 are obtained.

The final results are summarised below.

Table1 Carbon quotas for the thermal power sector by province in 2030

Province	Installed capacity （million kW）	Energy consumption (million tons of standard coal)	Number of employed persons (persons)	Thermal power generation (billion kilowatt hours)	Carbon Quota (million tons)
Beijing	1228.28	1305.09	100090.45	489.55	3536.10
Tianjin	1880.47	1491.92	32998.58	707.56	5064.89
Hebei	5220.25	8332.75	159928.87	2966.87	16989.28
Shanxi	7559.43	8543.20	188407.21	3252.47	26042.14
Inner Mongolia	10242.97	21943.59	132248.98	6145.84	66190.03
Liaoning	3549.16	5081.21	137286.26	1590.83	10891.23
Jilin	1943.82	1812.85	65679.65	777.06	5426.58
Heilongjiang	2413.49	2677.31	82977.54	1010.59	6967.36
Shanghai	2511.35	2094.47	23343.56	690.40	6840.13
Jiang Su	11696.90	13375.47	82447.71	4912.67	38744.60
Zhejiang	6142.46	7060.00	58577.20	2768.89	18447.62
An Hui	5131.47	7957.61	82235.83	2909.30	15591.30
Fujian	3507.52	4548.29	122252.89	1349.80	10618.19
Jiangxi	2692.38	3960.81	78197.41	1742.58	7911.85
Shandong	9380.06	13426.87	322399.83	7572.09	51019.01
Henan	7699.72	6737.66	202986.90	2080.85	25438.20
Hubei	3435.28	3868.72	116527.25	1890.96	10291.14
Hunan	2481.94	13966.04	110842.95	889.25	8707.63
Guangdong	9814.20	8930.51	136841.60	3880.80	29666.23
GuangXi	2406.81	3242.41	83046.07	1077.51	7017.33
Hainan	480.51	688.43	18251.60	239.32	1330.20
Chongqing	1388.44	1588.08	53604.94	730.79	3800.34
Si Chuan	1484.06	1303.51	173476.30	572.75	4602.40
Guizhou	3982.21	4199.23	78414.79	1477.11	11711.21
Yunnan	1355.92	1423.63	120036.34	356.30	3998.60
Shanxi	5562.66	4497.89	119898.37	2105.53	16633.78
Gansu	2154.36	1911.29	76804.93	815.77	6081.11
Qinghai	546.43	363.40	20186.53	120.94	1149.60
Ningxia	4142.44	7883.63	19868.33	1910.72	12640.20
Xinjiang	6365.53	11373.50	119695.39	3153.99	19885.77

RESULTS AND DISCUSSION

Initial Carbon Allowance Allocation Efficiency Analysis

The efficiency values were calculated using DEAP 2.1 as well as MAX DEA software and the final results are summarised below.

Analyzed from a regional perspective, the average efficiency values of each region are 0.8625 in the east, 0.8430 in the west, 0.8282 in the central and 0.5852 in the northeast, and the national average is 0.8207. The average efficiency values of the east, west and central regions are all on par with the national average efficiency value, indicating that the carbon quota efficiency gap of the thermal power industry in these three regions is not large and the development is more balanced, only the northeast region The efficiency value is more obvious from the national average efficiency value, which indicates that the development of thermal power industry in the northeast region is less coordinated with the carbon quota and does not match. The average carbon quota of each region is 168,374,965,000 tons in the east, 139,435,799,000 tons in the west, 163,175,924,000 tons in the center, and 111,913,831,000 tons in the northeast, with a national average of 15,107.8. Similar to the analysis of the average efficiency value, the difference between the average carbon quota in the east and center is small and almost negligible, and they are all larger than the national The average value is slightly lower in the west than in the east and central parts, and also slightly lower than the national average, and significantly lower in the northeast than in the east and central parts as well as the national average, indicating that the east and central parts can ensure higher efficiency despite the high carbon quota amount, and according to the idea of efficiency priority, more carbon quotas can be allocated to the east and central parts; while the efficiency value is low in the northeast, and the allocation of carbon quotas should be reduced.

Table2 Efficiency of initial carbon allowance allocation in 2030

Region	Province	Initial Carbon Allowance (million tons)	Initial efficiency	Region	Province	Initial Carbon Allowance (million tons)	Initial efficiency
East	Jiang Su	32748.20	1.0000	Western	Shaanxi	14059.41	1.0000
	Shandong	43122.99	1.0000		Yunnan	3379.74	1.0000
	GuangDong	25074.87	1.0000		Qinghai	971.69	1.0000
	Shanghai	5781.50	1.0000		Neimenggu	55945.99	1.0000
	Tianjin	4657.68	0.9199		SiChuan	3890.10	1.0000
	Zhejiang	18087.47	0.8668		Guizhou	11618.95	0.8552
	Fujian	11721.01	0.7704		Ningxia	14711.82	0.7327
	Beijing	3978.73	0.7528		Chongqing	4474.07	0.7200
	Hebei	21426.85	0.6808		Gansu	7672.04	0.6737
	Hainan	1775.66	0.6341		Guangxi	8950.83	0.6671
Central	Henan	21501.20	1.0000		Xinjiang	27704.73	0.6241
	Hunan	7359.98	1.0000	North East	Liaoning	14994.15	0.6219
	Shanxi	26772.55	0.8309				
	Hubei	11420.99	0.7662		Heilongjiang	10040.49	0.5920
	Jiangxi	8820.36	0.7618				
	An Hui	22030.47	0.6101		Jilin	8539.50	0.5418

When analysed from a provincial perspective, as with carbon quotas, there is a clear disparity in the efficiency of initial carbon quota allocation across provinces. The number of provinces with an initial carbon quota efficiency of 1 is 11, namely Jiangsu, Shandong, Guangdong, Shanghai, Henan, Hunan, Shaanxi, Yunnan, Qinghai, Inner Mongolia and Sichuan, in contrast to Jilin, which has the lowest initial carbon quota efficiency of 0.5418. and Heilongjiang, also numbering nine. Of the remaining 10 provinces, 9 have efficiency values between 0.7 and 0.9, indicating that the efficiency of carbon quota allocation in the thermal power sector is more polarised between provinces.

Analysis of redistribution process and results

Using the carbon quota allocation formula in the ZSG-DEA model and after 7 iterations, the efficiency of carbon quota allocation in each province was made to reach 1. The final results are shown in Table 3 below.

Table3Comparison table of carbon quota and efficiency values after iteration

Province	Actual carbon emissions (million tons)	ZSG allocation quota (million tons)	Difference (million tons)	Actual efficiency	efficiency after ZSG allocation	Difference
Beijing	3978.73	3536.10	-442.63	0.7528	1.00	0.2472
Tianjin	4657.68	5064.89	407.20	0.9199	1.00	0.0801
Hebei	21426.85	16989.28	-4437.57	0.6808	1.00	0.3192
Shanxi	26772.55	26042.14	-730.41	0.8309	1.00	0.1691
Neimeng	55945.99	66190.03	10244.04	1.0000	1.00	0.0000
Liaoning	14994.15	10891.23	-4102.92	0.6219	1.00	0.3781
Jilin	8539.50	5426.58	-3112.93	0.5418	1.00	0.4582
Heilongjiang	10040.49	6967.36	-3073.14	0.5920	1.00	0.4080
Shanghai	5781.50	6840.13	1058.63	1.0000	1.00	0.0000
Jiang Su	32748.20	38744.60	5996.40	1.0000	1.00	0.0000
Zhejiang	18087.47	18447.62	360.15	0.8668	1.00	0.1332
An Hui	22030.47	15591.30	-6439.17	0.6101	1.00	0.3899
Fujian	11721.01	10618.19	-1102.82	0.7704	1.00	0.2296
Jiangxi	8820.36	7911.85	-908.52	0.7618	1.00	0.2382
Shandong	43122.99	51019.01	7896.02	1.0000	1.00	0.0000
Henan	21501.20	25438.20	3937.00	1.0000	1.00	0.0000
Hubei	11420.99	10291.14	-1129.85	0.7662	1.00	0.2338
Hunan	7359.98	8707.63	1347.65	1.0000	1.00	0.0000
Guangdong	25074.87	29666.23	4591.37	1.0000	1.00	0.0000
GuangXi	8950.83	7017.33	-1933.50	0.6671	1.00	0.3329
Hainan	1775.66	1330.20	-445.47	0.6341	1.00	0.3659
Chongqing	4474.07	3800.34	-673.73	0.7200	1.00	0.2800
Si Chuan	3890.10	4602.40	712.30	1.0000	1.00	0.0000
Guizhou	11618.95	11711.21	92.26	0.8552	1.00	0.1448
Yunnan	3379.74	3998.60	618.85	1.0000	1.00	0.0000
Shanxi	14059.41	16633.78	2574.37	1.0000	1.00	0.0000
Gansu	7672.04	6081.11	-1590.94	0.6737	1.00	0.3263
Qinghai	971.69	1149.60	177.91	1.0000	1.00	0.0000
Ningxia	14711.82	12640.20	-2071.62	0.7327	1.00	0.2673
Xinjiang	27704.73	19885.77	-7818.96	0.6241	1.00	0.3759

Combining the data in the table, in order to be able to compare the changes in carbon quotas between provinces more visually, the following Figure 1 is drawn.

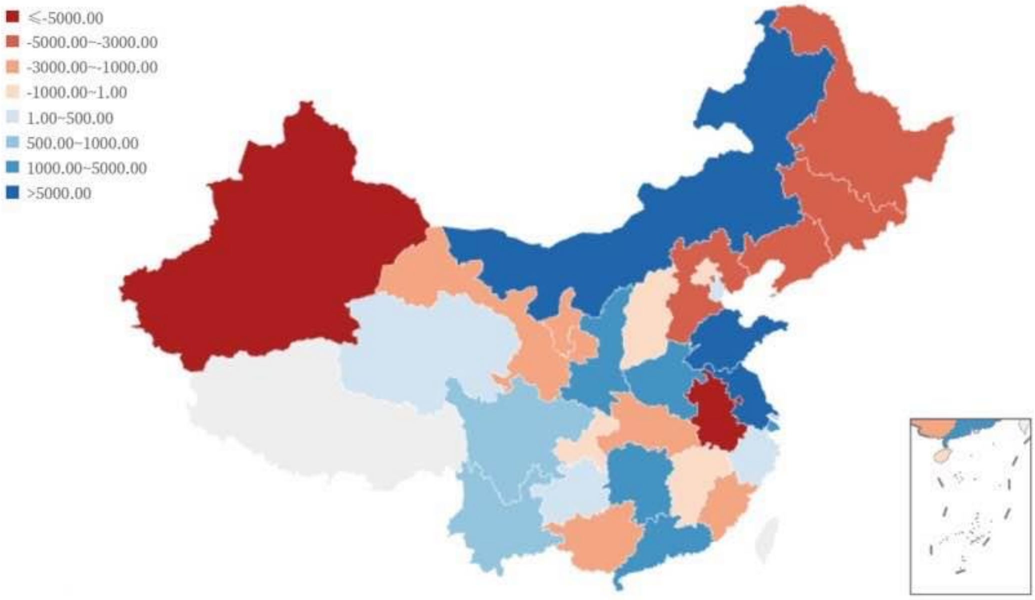

Fig.1Comparison of carbon quota changes

Through the analysis of Table 3 and Figure 1, the following conclusions can be drawn.

1. through the reallocation of ZSG-DEA model, the carbon emission allowances of 30 provinces have either increased or decreased compared with the initial carbon allowances, and their increases and decreases are listed in column 4. Among them, there are a total of 14 provinces that need to increase their carbon allowances, namely: Inner Mongolia, Shandong, Jiangsu, Guangdong, Henan, Shaanxi, Hunan, Shanghai, Sichuan, Yunnan, Tianjin, Zhejiang, Qinghai, and Guizhou. Most of these provinces are the eastern coastal provinces in China with relatively developed economies and high carbon emission efficiency, such as Tianjin, Shanghai, Jiangsu, Zhejiang, and Guangdong. With the rapid growth of residents' income, these provinces pay more attention to the improvement of living environment. As a result, these provinces have implemented stricter environmental regulation policies during the 11th to 13th Five-Year Plan period. Compared to the central and western provinces, they have placed more emphasis on the environmental requirements of production technologies and investment in dedicated technologies for environmental protection and pollution control in their industries, ranking higher in terms of efficiency nationwide. In Qinghai's economic structure, industry accounts for a relatively low share of the economy, which has a good environmental profile and relatively high efficiency. Therefore, the 14 provinces mentioned above should increase their carbon emission allowances according to the figures in column 4, based on the efficiency allocation proposed in this paper. For example, Jiangsu should increase its carbon emission quota by 5,996.4 million tons on top of the original initial carbon quota.

2. The provinces whose carbon allowances should be reduced are the remaining 16, which are: Beijing, Hainan, Chongqing, Shanxi, Jiangxi, Fujian, Hubei, Gansu, Guangxi, Ningxia, Heilongjiang, Jilin, Liaoning, Hebei, Anhui, and Xinjiang. Most of these provinces are economically underdeveloped and relatively inefficient in the central and western regions of China. For example, Liaoning is located in northeast China, and its industrial structure accounts for a high proportion of heavy industries such as mineral resource development and metal smelting, resulting in high carbon intensity and low carbon emission efficiency. Shanxi, Inner Mongolia and Shanxi have been the major coal resource supplying provinces in China. These three provinces supply 65% of the total coal resources consumed in China. The good fossil energy endowment has led these three provinces to concentrate on the development of their main industries, most of which are energy intensive, which is the main reason for the low efficiency of these three provinces. Gansu, Guangxi, Ningxia and Xinjiang are the typical economically underdeveloped provinces in western China, whose economic systems have long lagged behind in total factor productivity and have low quota allocation efficiency. Therefore, the above 15 provinces should reduce their carbon emission allowances according to the efficiency allocation proposed in this paper and according to the figures in column 4.

3. Further analysis of the amount of carbon allowance changes in each province and the initial carbon allowance efficiency shows that all provinces that need to increase carbon allowances are provinces with high initial efficiency, and they include all 11 provinces with an initial efficiency of 1, and the efficiency of the other three are above 0.85; on the contrary, all provinces that need to reduce carbon allowances are provinces with low initial efficiency values, although there is no linear relationship between the initial efficiency and the carbon allowance

Although there is no linear relationship between the initial efficiency and the amount of carbon quota change, the overall trend shows that there is a positive relationship between the two. It can also be seen that the ZSG-DEA model constructed in this paper is a carbon quota allocation scheme based on the efficiency principle, and "the higher the efficiency value, the more carbon quotas need to be increased", which is indeed the viewpoint of pursuing efficiency.

CONCLUSION

In this paper, an improved gray prediction model is used to forecast the data of four main indicators of thermal power industry, and then the ZSG-DEA model is used to evaluate the carbon quota allocation efficiency.

1. The results of the initial carbon quota allocation efficiency measurement in 2030 show that there is a large gap in carbon quota allocation efficiency among different provinces in China, and the analysis by dividing into regions shows that the reasons for this gap may be related to geographical location, technology level and economic development.

2. Carbon quota reallocation through ZSG-DEA model can effectively improve the efficiency of carbon quota allocation in inefficient provinces. The 16 provinces located in the economically underdeveloped central and western regions of China with relatively low efficiency of carbon quota allocation, such as Hebei and Anhui, need to reduce their carbon quotas when allocating efficiently through the ZSG-DEA model, while the 14 provinces with relatively more developed economies and high efficiency of carbon quota allocation, such as Guangdong and Shandong, should increase their carbon emission quotas.

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