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Evaluation of regional carbon efficiency based on dea-vrs model- a case study of china's 30 provinces

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ABSTRACT

In order to increase comparability among different regions, DEA-VRS model is applied to evaluate regional carbon efficiency. The innovation of this paper is selected relative amount input and output index to ensure the comparison objectively. The input indicators relevant to urbanization, the proportion of R & D and environmental investment, per capita road area and green area, green coverage rate, as well as the propitiation of tertiary industry, employees and high energy consumption industries. The output indicators relative to population, GDP and per capita disposable income of every one carbon emissions. Then 30 provinces from 2001 to 2011 are selected as case to be evaluated with the results that the overall efficiency of the cases upward after the first fall and the proportion of environmental protection investment, R&D investment and high energy consumption industry are main factors restricting carbon efficiency improved.

KEYWORDS

Carbon efficiency; Dea-vrs model; Input and output indicators.

INTRODUCTION

Today, carbon efficiency is a hot issue between governments and academia. In many researches, as a useful tool, DEA method has been applied in evaluating carbon efficiency in industries[1-3] and regions [4]level. However, most studies so depend on absolute output and input indicators that the evaluation results are difficult to objectively reflect the difference of carbon efficiency among different regions. In order to improve the shortage, the paper selected relative amount input and output indicators to evaluate and compare carbon efficiency of different regions.

METHODOLOGY

DEA-VRS Method Introduction

Data envelopment analysis (DEA) is an efficiency evaluation method whose basic linear programme to calculate decision-making production frontier with the judgment that DEA is efficiency only when the efficiency's value which falls on boundary is equal to 1. Otherwise, DEA' efficiency is between 0 to 1. According to the calculation returns to the scale, the model can be divided into Data envelopment analysis-Constant returns to scale (DEA-CRS) and Data envelopment analysis-Variable returns to scale (DEA-VRS). This paper used DEA-VRS model to evaluate carbon efficiency. The basic model is as follows:

Suppose that there are n DMUj {j=1, 2,..., n} and each DMUj has m types of input xj={x1j, x2j,..., xmj} and s kinds of types of output yj={y1j, y2j,..., ysj}, DMUj0 conducted on a model of efficiency evaluation are:

$$
\begin{aligned}
&\operatorname{Max}\theta \\
&s.t. \sum_{j=1}^{n} \lambda_j \cdot x_j \le x_0 \\
&\sum_{j=1}^{n} \lambda_j \cdot y_j \ge \theta y_0,\ \lambda_j \ge 0,\ j = 1,2,\ldots n \\
&\sum \lambda_j = 1
\end{aligned}
\tag{1}
$$

In equation (1), $x_{ij} \geq 0$ and x_{ij} represents the i input variable of the j decision unit DMU_j, $y_{ij} \geq 0$ and y_{ij} represents the i output variable of DMU_j, θ is a standard value which is greater than 0 and less than 1, λ is a constant vector which constructs of n×l.

Index Selection

We choose input indicators from seven aspects, including city structure, municipal, greening, industrial structure, energy consumption, technology and environmental protection. The input indicators include the per capita road area and the per capita green area as density indicators, select urbanization rate, green coverage rate, the proportion of tertiary industry, the proportion of employees, the proportion of energy-intensive industries, R & D investment proportion of the total investment and environmental protection investment proportion of total investment as relative indicators.

Besides, we choose three relative output indicators which were population capacity of per carbon emissions, GDP output of per carbon emissions and per capita disposable income of per carbon emissions.

CASE STUDY

We chose China's 30 provinces or municipal cities as the research object, conducted regional carbon efficiency evaluation and trend analysis from 2001 to 2011.

Data Collection and Treatment

The index values were obtained from "China Statistical Yearbook", "China Environment Statistical Yearbook", "China Industrial Economy Statistical Yearbook", "Chinese Energy Statistical Yearbook" as well as the provinces statistical yearbook. All statistical yearbooks were from 2002 to 2012.

In this paper, DEAP (VERSION2.1) software was used to calculate the carbon efficiency of the cases and then we selected typical year 2001, 2006 and 2011 to analyze.

Evaluation of Carbon Efficiency

TABLE 1: Carbon comprehensive efficiency of 30 provinces

year	**Bei jing**	**Tian jin**	**He bei**	**Shan xi**	**Inner Mongolia**	**Liao ning**	**Ji lin**	**Heilong jiang**	**Shang hai**	**Jiang su**
2001	0.980	0.903	0.849	1.000	1.000	0.619	0.864	0.836	0.827	1.000
2006	1.000	1.000	0.763	0.603	1.000	0.728	0.987	1.000	0.984	1.000
2011	1.000	0.993	0.720	0.666	0.834	0.827	1.000	1.000	1.000	0.887
year	Zhe jiang	An hui	Fu jian	Jiang xi	Shan dong	He nan	Hu bei	Hu nan	Guang dong	Guang xi
2001	0.986	1.000	0.994	1.000	0.800	0.967	0.627	1.000	0.898	1.000
2006	1.000	0.959	0.936	1.000	0.734	0.949	0.704	0.907	0.948	1.000
2011	0.835	0.941	0.729	1.000	0.664	0.911	0.832	1.000	0.824	1.000
year	Hai nan	Chong qing	Si chuan	Gui zhou	Yun nan	Shaan xi	Gan su	Qing hai	Ning xia	Xin jiang
2001	1.000	1.000	1.000	0.903	1.000	0.769	0.683	1.000	1.000	0.992
2006	1.000	1.000	0.962	1.000	1.000	0.799	0.647	0.993	0.553	0.836
2011	1.000	1.000	1.000	1.000	1.000	0.701	0.884	0.857	0.488	0.656

(Remark: Comprehensive efficiency shows carbon efficiency)

TABLE 1 reflects the carbon efficiency evaluation results of 30 provinces in the year of 2001, 2006 and 2011. If comprehensive efficiency value was “1”, it said the regional carbon efficiency was DEA effective.

As shown in the TABLE1, in 2001, DEA effective areas included 13 provinces: Shanxi, Inner Mongolia, Jiangsu and so on. In 2006, carbon efficiency of DEA effective set contained 12 provinces: Beijing, Tianjin, Inner Mongolia and so on. In 2011, DEA effective areas included 12 provinces: Beijing, Jilin, Heilongjiang and so on.

From the DEA comprehensive results, the numbers of DEA effective provinces was not changed significantly from 2001 to 2011, but the geographical distribution changed greatly. In the cases, the comprehensive efficiency of Jiangxi, Guangxi, Hainan, Chongqing and Yunnan were “1” in three years, carbon efficiency reached the optimum state. There were 7 provinces, including Beijing, Jilin, Heilongjiang, Shanghai, Guizhou, Liaoning and Hubei showed an increasing trend year by year, and with the exception of Liaoning and Hubei, the other 5 provinces finally reached the highest carbon efficiency that DEA effective. Comprehensive efficiency value of Shanxi, Inner Mongolia, Jiangsu, Anhui, Hunan, Sichuan, Qinghai and Ningxia was “1” in 2001, but as time went on, in addition to Sichuan and Hunan, carbon efficiency of the rest 6 provinces were different degrees of decline. Other provincial comprehensive efficiency value was showing a decline or volatility decline.

Frontier production projection analysis

For DEA invalid provinces, DEAP software was applied to adjust the original input and output vector to DEA effective. Adjusted points were projection in the production frontier. Because the differences among provinces in many aspects were so big that the absolute value in the production frontier - the amount of redundancy of each input factor reached to the balance can not be compared objectively. Therefore, we still used the relative amount that the rate of each input factor redundancy as basic variables to make the wind rose diagram and analyze the reasons causing the low carbon efficiency.

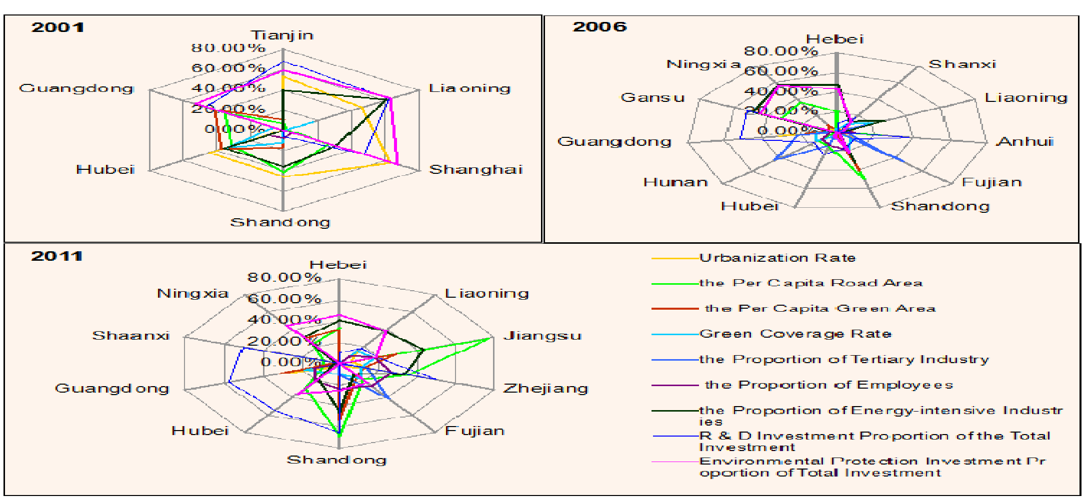

Figure 1 : The Wind Rose Diagram

As shown in Figure 1, in 2001, DEA invalid was mainly caused by the disproportionate of environmental protection investment and R&D investment, the proportion of high energy consumption industries was too high and urbanization rate was large redundant. In addition, per capita road area and per capita green area were slightly redundant. In 2006, DEA invalid was still mainly caused by environmental protection investment and R&D investment not reasonable and high energy consumption industries output value was too high. Compared with 2001, redundancy of investment in environmental protection, R & D investment and eight energy industries output value were all declined, especially the rate of urbanization redundancy declined significantly. However, per capita road area and the proportion of tertiary industry had larger redundancy. In 2011, DEA invalid was still mainly caused by low efficiency of environmental protection investment and R&D investment. Furthermore, the rate of redundancy larger than the 2006. Redundancy about the proportion of energy-intensive industries was too high, but slightly reduced. Per capita road area lager redundancy was another reason. But compared with 2006, the rate of tertiary industry output value tends to be more reasonable and redundancy decreased significantly.

Suggestion Proposed

From above study, we could draw that in order to improve the cases regional carbon efficiency, the following aspects should be considered specifically:

Firstly, environmental protection investment and R & D investment cannot play a role alone, it requires considering all aspects of a city in one package in the same phase. Otherwise, the strange scene may be appear that the more input, the less efficiency. Reasonable investment could play an important role in improving regional carbon efficiency.

Secondly, today, high energy consuming industries means large CO_2 emissions and heavily pollution. Therefore, we should speed up the transformation and development of these industries to improve energy-saving and environmental protection level of production equipment and reduce CO_2 emissions. Meanwhile, we should control pollution treatment and discharge process strict, and reduce pollution index in these sectors to improve the production efficiency of industries.

Thirdly, adjacency inter-provincial transfer of industries, provinces could play their own advantages and achieve mutual promotion of industrial development. More and more rational industrial structure has a positive effect on improving carbon efficiency.

CONCLUSIONS

The cases study proved that comparing with absolute value, selected relevant value as input and output indicators in DEA-VRS model for regional carbon efficiency evaluation could be more exact and objective reflect the difference among the different areas. Furthermore, the main factors which influenced the efficiency in a high level could be more easy found and adjustment advise would be concrete and available.

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