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A comparative analysis of China's regional energy and emission performance: Which is the better way to deal with undesirable outputs?

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Abstract:Measuring and improving the energy performance with considering emission constraints is an important issue for China's energy conservation, pollutant emissions reduction and environment protection. This study utilizesseveral data envelopment analysis (DEA) based models to evaluate the total-factor energy and emission performance of China's30 regions within a joint production framework of considering desirable and undesirable outputs as well as separated energy and non-energy inputs. DEA window analysis is applied in this study to deal with cross-sectional and time-varying data, so as to measure the performance during the period of 2000-2009. Twotreatmentsfor undesirable outputs are combinedwith DEA models and the associated indicators for simplex energy performance and unified energy and emission performance measurement are proposed and compared. The evaluation results indicate that the treatment of undesirable outputs transformation is more appropriate for China's regional energy and emission performance evaluation because it has stronger discriminating power and can provide more reasonable evaluation results that characterize China's regions. The empirical result shows that east Chinahas the highest and the most balanced energy and emission performance. The energy and emission performance of Chinaremained stable during 2000-2003, decreased slightly during2004-2006, and hascontinuously increased since 2007.

Keywords: Energy efficiency; CO_2emissions;Performance evaluation

1 introduction

Global warming is one of the world's most important environmental problems at present andit is largely attributed to emissions of greenhouse gases such as carbon dioxide (CO_2) from the burning of fossil fuels. In recent years, a growing number of researches have focused on issues of energy efficiency evaluation, which are considered a crucial approach to reducing CO_2 emissions and mitigating global climate change.

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Despite the major energy efficiency improvements achieved by China during the last two decades, the rapid development of economy since the implementation of the economic reform policy in 1978 has substantially increased China's primary energy consumption and led to serious environmental problems both at the national and regional levels of the country due to the annually increasing emissions of,for example, CO_2 and SO_2. Nowadays, China has become the second largest economy,and the greatest consumer of energy and emitter of CO_2 in the world (Liao et al., 2007). Moreover, with the growing emphasis on international environmental issues from public and governments, China has faced tremendous pressures in international negotiations on emissions reduction and climate change mitigation.

To improve energy utilization efficiency, protect the environment, and realize sustainable development, the Chinese government has put forward a strategic targetof constructing a resource-saving and environment-friendly society. Therefore, the State Council of China announced that Chinaaimed to reducethe energy consumption per unit of GDP by 32% by the year 2015, and to reduce the CO_2 emissions per unit of GDP by 40-45% by the year 2020, with both targets based on the 2005 levels. Following this, the targets of energy saving and emission reduction were given a legal force for further listing in China's National Economic and Social Development Medium- and Long-term Plan.Therefore,evaluating and improving energy efficiency,and taking environment constraintsinto consideration,is quite important for China to slow down the rapid growth of primary energy consumption and CO_2 emissions.

According to Ang (2006), a monetary-based energy efficiency indicator,represented by the energy consumption per unit of current output, is often used to measure the economy-wide energy efficiency at the macro level. For example, energy intensity,defined as the energy consumption divided by the economic output, is a commonly-used indicator for energy efficiency.This conventional energy efficiency indicator takes energy consumption into account as a single input(but ignores some other essential inputs such as capital and labor) to produce economic outputs. Therefore, this indicator provides only single- or partial-factor energy efficiency. However, any economic production activity is a joint-production process which utilizes energy resources (coal, oil, nature gas, etc.) and other non-energy resources (labor and capital) to produce desirable outputs (e.g., GDP) and undesirable outputs as the pollutant emissions (CO_2, SO_2, etc.). Therefore, a total-factor efficiency evaluation model will be more appropriate. In addition, as indicated by Boyd and Pang (2000),Sueyoshi and Goto (2011), and Wang et al. (in press),the improvement of energy efficiency as well as environment efficiency mainly relies on a total-factor productivity improvement.Here, the term "total-factor" implies that three key input factors of energy, capital and labor, as well as the economic output factor of GDP are all included in the evaluation and the total-factor productivity improvement is considered. The term "total-factor energy efficiency" implies that energy efficiency is defined as the actual energy input divided by the target energy input (i.e. optimized energy input located on the efficiency frontier) and measured within the total-factor framework.

Furthermore, considering the emissions of CO_2 and SO_2 as by-products associated with economic output,emissionefficiency should not be neglected when evaluating energy efficiency, so as to provide a more appropriate and reasonable performance measure. Similar to the definition of energy efficiency, here, the emission efficiency is defined as the actual undesirable output emission divided by the target output emission. Thus, the total-factor efficiency evaluation model should also be capableof measuring the integrated energy and emissionefficiency.

Data envelopment analysis (DEA),first proposed by Charnes et al. (1978),has recently been widely applied at the macro-economy level to study the energy and environment efficiency.It provides an appropriate framework to combine multiple inputs and multiple outputs in examining relative efficiency of decision making unit (DMU). Hu and Wang (2006) proposedthefirst DEA based total-factor energy efficiency evaluation modelfor China's provincial energy efficiencymeasurement. Their model treated energy consumption and GDP as normalinput and desirable output without considering any undesirable output. Zhou et al. (2008) developed several DEA-based environment efficiency evaluation models for the measurement of the carbon emission efficiency of several world regions. In their models,the outputs were separated into desirable and undesirable ones, however, only the energy inputs are included,while the non-energy inputsare omitted. Zhou and Ang (2008) further proposed several linear programming models within a joint production framework for measuring economy-wide energy efficiency.

The aforementioned studies proposed only an individual evaluation of energy efficiency or environment efficiency rather than providing anintegrated energy and environment efficiency measurement. Recently, some newly-developed DEA models have been applied in the integratedenergy and environment efficiency evaluation. For example, based on a non-radial DEA framework, Zhou et al. (2007) evaluated the energy and environment efficiency of 26 OECD countries from 1995 to 1997. The factors of labor, primary energy consumption, GDP, CO_2, sulphur oxides, nitrogen oxides and carbon monoxide were all included as input or outputfactors in their study. By utilizing the traditional BCC model (Banker et al., 1984), Yeh et al. (2010) compared the regional energy and environment efficiency between mainland China and Taiwan. In their model, the undesirable outputs were mathematically transformed following Seiford and Zhu (2002), before they were involved in the operationof the BCC model, in order to increase desirable outputs and decrease undesirable outputssimultaneously. However, Yeh et al. (2010) did not consider the maximization of energy conservation because when calculating energy efficiency, these non-energy inputs were not separated from energy inputs,hence, all the inputs had to be contracted together. Because the energy resources that serve as input are usually non-renewable, but the non-energy resources such as labor and capital are renewable in actual production process, these two kinds of inputs should be separated and the non-renewable energy should be saved as much as possible to improve energy utilization efficiency and reduce pollutant emissions.

Most recently, Bian and Yang (2010) evaluated the aggregated resource and environment efficiency of 30 Chinese provinces byusing radial and non-radial DEA models and Shannon's entropymethod to integrate different evaluation results from different DEA models. Shi et al. (2010) measured overall technical efficiency, pure technical efficiency, and scale efficiency of the energy and environment of 28 administrative regions in China through three extended DEA modelsin which the undesirable outputs were treated as inputs in order to be proportionally decreased with the energy inputs. Wang et al. (2011) evaluated China's regional energy and environment efficiency by utilizing the directional distance function approach,which attempts to proportionally increase desirable outputs and decrease undesirable outputs simultaneously along different directions toward the efficiency frontier. The research of Bian and Yang (2010) was a static analysis for, as theyevaluatedthe efficiency based on a single year's data, the time trend of the efficiency could not be seen in their results. Shi et al. (2010) and Wang et al. (2011) provided multi-period efficiency evaluationsin their studies.However they onlycalculatedthe efficiency scores of different regions foreach year and then simply compared each region's efficiencyin different years. Therefore, their results may lack comparability and, furthermore, have weak discriminating power.

In this current study, we propose severalDEA models which are used to measure simplex energy performance (without considering environment performance) and unified energy and emission performance (including environment factors) based on different treatments of undesirable outputs. We point out that,in our study,the energy performance is defined as the single performance of energy utilizationfor economic production, and the unified energy and emission performance is defined as theintegrated performance of both energy utilization (for economic production) and pollutantemissions (as by-products of production process). These two performances are evaluated in the form of energy and emission efficiency indicators constructed withthe DEA methods. In addition, the DEA window analysis technique and corresponding rank sum test are combined withtheseenergy and emission performance evaluation modelsin order to give a dynamic evaluation of the performances of 30 regions in China during the period of 2000 to 2009. Furthermore, the performance evaluation results from different models are compared to give a comprehensive analysisof the advantages and disadvantages of the utilized undesirable outputs treatments and the associated performance indicators.

The rest of this paper is organized as follows. Section 2 presents the energy and emission performance evaluation models, DEA window analysis and rank sum test for dynamicperformance evaluation. Section 3 presents the data and variables, and describes the developments of China's regions and areas. Then, China's regional simplex energy performance and unified energy and emissionperformance is measured, compared and discussed in Section 4. Section 5 concludes this paper.

2 DEA based methods for energy and emission performance evaluation

2.1 Energy performance evaluation model

The DEA method is a non-parametric mathematical programming approach used to evaluate a set of comparable decision-making units (DMUs). Suppose there are n DMUs, denoted by DMU$_j$ (j=1,…,n), and each of them represents an administrative region of China. Every DMU uses m non-energy inputs x_{ij} (i=1,2,…,m) and L energy inputs e_{lj} (l=1,…,L) to produce s desirable or good outputs y_{rj} (r=1,…,s) anddischarge$K$ undesirable or bad outputs b_{kj} (k=1,…,K). Then, the energy performance could be measured as follows.

$$
\begin{aligned}
&\min \theta \\
&s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-} = x_{ij_0}, i = 1, ..., m, \\
&\qquad \sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e-} = \theta e_{lj_0}, l = 1, ..., L, \\
&\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y+} = y_{rj_0}, r = 1, ..., s, \qquad (1) \\
&\qquad \sum_{j=1}^{n} \lambda_j b_{kj} = b_{kj_0}, k = 1, ..., K, \\
&\qquad \sum_{j=1}^{n} \lambda_j = 1, \\
&\qquad \lambda_j, s_i^{x-}, s_l^{e-}, s_r^{y+} \geq 0, \text{for all } j, i, l, r.
\end{aligned}
$$

Here, $\lambda_j (j = 1, ..., n)$ is the intensity variables associated with each DMU*j* for connecting the inputs and outputs by a convex combination. $s_i^{x-} (i = 1, ..., m)$, $s_l^{e-} (l = 1, ..., L)$, and $s_r^{y+} (r = 1, ..., s)$ are slack variables associated with non-energy inputs, energy inputs and desirable outputs, respectively.In Model (1), the inputs regarding the *j*th DMU are separated into non-energy and energy parts, and the outputs are separated into desirable and undesirable parts. In addition, Model (1) provides the energy efficiency θ with the undesirable outputs fixed. Letting（$\theta^*, \lambda_j^*, s_i^{x-*}, s_l^{e-*}, s_r^{y+*}$) be the optimal solutions of Model (1), then the Energy Performance Indicator (*EPI*) could be defined as $EPI = \sum_{l=1}^{L} \alpha_l \, (\theta^* e_{lj} - s_l^{e-*}) / e_{lj}$. Here, α_l is the normalized user specified weights associated with energy input e_l, which reflect the importance of each energy resource in the energy performance evaluation.

2.2 Energy and emission performance evaluation model

Now, we consider not only the energy performance but the emission performance. In the production process, a DMU prefers to produce desirable outputs as much as possible, and to consume resource inputs as little as possible. However, the primary energy resources consumed in China aremainly non-renewable ones, such as coal and oil, and the burning of these energy resources usually generates waste gas like CO_2 and SO_2. Therefore, when measuring the energy and emission performance, people always hope to reduce the energy consumption as much as possible for a given amount of desirable outputs and non-energy inputs. And for the undesirable outputs, the less of them is preferable. However, in standard DEA models, to directly reduce the undesirable outputs of pollutant emissions is not allowed.

There are several methods can deal with this difficulty. The first one is to treat the undesirable outputs as inputs, and this approach is the most widely used one in the environment efficiency measurement (Hailu and Veeman, 2001; Bian and Yang, 2010; Shi et al., 2010).The second one is to use the reciprocals of the undesirable outputs in standard DEA model. Färe et al. (1989) firstly introduced a non-linear programming approach to deal with undesirable outputs.This approach is also known as hyperbolic measure. The third one is first to transform undesirable output variables into new variables similar to desirable output variables, which have the same variation directions, and then apply standard DEA model to solve a linear programming. Seiford and Zhu (2002) developed such a DEA model,which mathematically transforms the undesirable outputs into desirable outputs under the classification invariance.This approach is also widely used in environment efficiency evaluation (Jahanshahloo et al., 2004; Hua et al., 2007; Yeh et al., 2010).The fourth one is to applythe directional distance function to measure the environment efficiency by simultaneously increasing desirable output productions and reducing undesirable output emissions. This approachwas firstly proposed by Chung et al. (1997) and further discussed in Färe et al. (2007).

Forthe second approach above, the related DEA model is a non-linear programming which may be difficult tosolve and this model have shortcomings when measuring energy and emission performance simultaneously. For the fourth approach above, the evaluation resultsrely toa great extent on the choice of directional distance function. Different functions may lead to very different efficiency evaluation results for the same DMU,and the choice of directional distance functions depends on the subjective preferenceand judgment of the evaluator. Therefore, in our study, the first and third approaches are chosen as the basic techniques to deal with undesirable outputs and the corresponding DEA models are applied to comparatively analyzeChina’s regional energy and emission performance.

Here, we consider that the undesirable outputs of CO_2 and SO_2 emissionscomemainly from the burning of fossil fuels in the industrial production process whichcould be reduced if energy consumption is reduced. Therefore, similar to Shi et al. (2010) and Bian and Yang (2010), we first propose the following Model (2) for unified energy and emission performance evaluation. Here we treat the undesirable outputs as “inputs” and make the energy inputs and undesirable “inputs”decrease simultaneously, but in different proportions.

$$
\begin{aligned}
& \min \theta^e + \theta^b \\
& s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-} = x_{ij_0}, i = 1,...,m, \\
& \qquad \sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e-} = \theta^e e_{lj_0}, l = 1,...,L, \\
& \qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y+} = y_{rj_0}, r = 1,...,s, \qquad\qquad (2) \\
& \qquad \sum_{j=1}^{n} \lambda_j b_{kj} = \theta^b b_{kj_0}, k = 1,...,K, \\
& \qquad \sum_{j=1}^{n} \lambda_j = 1, \\
& \qquad \lambda_j, s_i^{x-}, s_l^{e-}, s_r^{y+} \geq 0, \text{for all } j, i, l, r.
\end{aligned}
$$

In Model (2), θ^e is the energy efficiency and θ^b is the emissionefficiency.The definitions of other variables and parameters in Model (2) are same with those in Model (1). Model (2) attempts to proportionally decrease the amounts of energy inputs and emission outputs as much as possible for a given level of non-energy inputs and desirable outputs. Letting ($\theta^{e*}, \theta^{b*}, \lambda_j^*, s_i^{x-*}, s_l^{e-*}, s_r^{y+*}$) be the optimal solutions of Model (2), then the Unified Energy and Emission Performance Indicator (*UEEPI*1) for Model (2) could be defined as $UEEPI_1 = w_1 \sum_{l=1}^{L} \alpha_l (\theta^{e*} e_{lj} - s_l^{e-*}) / e_{lj} + w_2 \sum_{k=1}^{K} \beta_k \theta^{b*}$.Here, α_l and β_k are the normalized user specified weights associated with energy input e_l and undesirable output b_k , respectively, which reflect the importance of each energy resource and each pollutant emission in the energy and environment performance evaluation. In addition, w_1 and w_2 are also the normalized user specified weights to indicate the contributions of energy efficiency and environment efficiency in$UEEPI_1$.If $UEEPI_1 = 1$, then the related DMU is considered to be efficient and located on the efficiency frontier reflecting the best practice of energy utilization and pollutant emissions. If $UEEPI_1 < 1$, thenthe related DMU is considered to be inefficient,and may havethe potential to reduce energy consumption orpollutant emissions.

Model (2) treats the undesirable outputs as inputs which is reasonable when considering the emission of pollutant is a “right” for each region of China under the emission constraints and environment protection regulations, and that each region needs to “pay” for this “emission right”. However, this treatment is not consistent with the real production process in which the undesirable outputs are the by-products of desirable outputs. Therefore, we then develop another model for energy and emission performance evaluation, in which the emissions are first transformed following Seiford and Zhu (2002), and then the transformed emissions are treated as desirable outputs. The transformation processis as follows. First, each emission variable is multiplied by “-1”, and then, a proper translation vector *v* is added to the negative emission variables to make them positive. That is $\bar{b}_{kj} = -b_{kj} + v_k > 0$, k=1,…,K, which could be achieved by choosing $v_k = \max_j \{b_{kj}\} + 1$, k=1,…,K.Under the variable returns to scale assumption, these two processes (position change and transformation) give the same efficiency frontiers. The corresponding performance evaluation model is the following.

$$
\begin{aligned}
& \min \theta^e - \theta^b \\
& s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x-} = x_{ij_0}, i = 1, ..., m, \\
& \qquad \sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e-} = \theta^e e_{lj_0}, l = 1, ..., L, \\
& \qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y+} = y_{rj_0}, r = 1, ..., s, \qquad\qquad (3) \\
& \qquad \sum_{j=1}^{n} \lambda_j \bar{b}_{kj} = \theta^b \bar{b}_{kj_0}, k = 1, ..., K, \\
& \qquad \sum_{j=1}^{n} \lambda_j = 1, \\
& \qquad \lambda_j, s_i^{x-}, s_l^{e-}, s_r^{y+} \geq 0, \text{for all } j, i, l, r.
\end{aligned}
$$

Here, the variables and parameters in Model (3) have the same definitions of those in Model (2). Model (3) indicates that the amounts of energy inputs should be proportionally decreased by θ^e , and correspondingly the transformed emission outputs should be proportionally increased by θ^b so as to improve the Unified Energy and Emission Performance Indicator ($UEEPI_2$) for Model (3). Here, $UEEPI_2$ has a similar definition and an identical formulation as$UEEPI_1$. However, we have to point out that these two indicators are different unified energy and environment performance measures because they are obtained from different models which have different undesirable output treatments. Therefore, we will further compare these two indicators when they are applied to evaluate China's regional energy and emission performance in Section 4.

2.3 DEA window analysis and rank sum test

We plan to measure the energy and emission performance of different regions in China for a time period of 2000 to 2009, instead of a single year, in order to gain a deeper insight of the regional performance changes of China. Therefore, DEA window analysis technique will behelpful in detectingthe performance fluctuation.

DEA window analysis (Charnes and Cooper, 1985) is anextension of the traditional DEA approach which operates on a principle of moving averages and conduct efficiency measures by treating each DMU in different periods as a separate unit. Therefore, this technique iscapable of handlingcross-sectional and time-varying data andevaluating dynamic effects. In a window analysis framework, the performance of a specific region in a specific period can be contrasted with the performance of other regions as well as with its own performance in other periods. Therefore, by applying window analysis, the energy and emission performance of different regions in different years can be explored through a sequence of overlapping windows.

In this study, each window with $n \times w$ observations is denoted starting at time t ($1 \le t \le T$) with window width w ($1 \le w \le T\text{-}t$). Here,wehave 30 regions of China with the time period of 10 years' (2000-2009) efficiencies that require to be examined;thus$n$=30 and T=9. The window width is supported by the number of years under analysis. According to Zhang et al. (2011), since DEA window analysis implicitly assumes that there are no technical changes during the period of each window, areasonable narrow window width must be assigned. Charnes et al. (1994) proposed that a window width of three or four yearswould tend to yield the best balance of informativeness and stability of the efficiency measure.

In this study, we chose a window with the width of three (w=3) years, following Halkos and Tzeremes (2009), to get credible performanceevaluation results. Therefore, the first three years (2000-2002) construct the first window. Itthen moves on a one-year period by dropping the first year and adding a new year. Thus, the next three years(2001-2003) form the second window. This process continues until the last window (containing the last three years of 2007-2009) is constructed. Finally, eight windows are obtained for each region and the number of observations in each window becomes 90 ($n \times w$=30×3).

In order to ensure that three years' window width is reliable, we then use the Kruskal-Wallis rank sum test (K-W rank sum test for short) to examine whether the data pool for each window is justifiable. To compute the K-W statistic H, we reorder all the 90 "regions" in each window from the least to the greatest according to each region's value of EPI (or $UEEPI_1$, $UEEPI_2$). LettingR_{jt} denote the rank of the jth region in the tth period, and the rank sum of all regions in the tth period is calculated as $R_t = \sum_{j=1}^{n_t} R_{jt}$ where n_t stands for the number of regions at the tth period (n_t=30 in this study). Then, the K-W statistic H is computed as in equation (4).

$$H = \frac{12}{n(n+1)} \sum_{t=1}^{3} \frac{R_t^2}{n_t} - 3(n+1) \qquad (4)$$

Here, n stands for the total number of DMUs in all the annual periods of a window. Since we chose the window width as 3, t is from 1 to 3 in equation (4). The statistic H follows the χ^2 distribution with a degree of freedom df=2. When multiple observations have a same rank (i.e. the ranks of different DMUs have ties), the H statistic needs to be adjusted as in equation (5).

$$H^c = \left\{ \frac{12}{n(n+1)} \sum_{t=1}^{3} \frac{R_t^2}{n_t} - 3(n+1) \right\} \Bigg/ \left(1 - \frac{\sum(\tau^3 - \tau)}{n^3 - n} \right) \qquad (5)$$

where τ indicates the number of observations on a same rank. If the H score is less than the critical value of the χ^2 distribution at a given significance under the specific degree of freedom, then the null hypothesis could not be rejected, i.e., an performance measure has a same distribution during the observed annual periods in a window. As a result, such kind of test can confirm the validity of the window width so that we can aggregate all data sets of the three years' period as a single data set for DEA window analysis.A detaileddescription on the Kruskal-Wallisrank sum test could be found in Hollander and Wolfe (1999).

The measure of energy performance (EPI) and unified energy and emission performance ($UEEPI_1$) and ($UEEPI_2$)of 30 regions of China in each window can be obtained. For each region, each year has three values on the performance, with the exception of 2000 and 2009, which have only one value, and 2001 and 2008, which have two values. We can then calculate the mean value of eachperformanceindicatorfor each region in the same year so as to obtainthefinal value of energy and emission performance of 30 regionsof China.

3 Data, variables and descriptions of China's regions and areas

In this study, we use labor and capital stock as two non-energy inputs.Energy consumption, separated into coal, crude oil and nature gas,are used as three energy inputs.Gross domestic product (GDP) is utilized as desirable output, and carbon dioxide (CO_2) and sulfur dioxide (SO_2) emissions are considered as two undesirable outputs. The annual data on labor, energy, GDP (at 2000 price) and SO_2 emissions are obtained from the China Statistical Yearbook(2001-2010), the China Energy Statistical Yearbook (2001-2010), and the China statistical Yearbook on Environment (2001-2010). The annual data on capital stock of each region of China come from the results proposed by Shan (2008). Following Liu et al. (2010), we estimate the annual data on CO_2 emissions based on the amounts of fossil fuel(coal, crude oil, and nature gas) consumption, and the CO_2 emission factors for the fossil fuel combustion obtained from IPCC (2006).

In our study, 30 regions of China are examined.Tibet, Taiwan, Hong Kong and Macau are omitted due to the absence of relevant data on energy and emissions. Table 1 presents the summary statistics of input and output variables for specific four years in our study period. From the perspective of geography and economic development factors of China, its 30 regions are usually clustered into three major areas: the east, central, and west area, which are shown in Table 2.

Table 1 Summary statistics of inputs and outputs

Selected year	Variable	Non-energy inputs		Energy inputs			Desirable outputs	Undesirable emission outputs	
		Capital stock	Labor	Coal	Crude oil	Nature gas	GDP	CO_2	SO_2
	Units	Billion RMB	Million employees	Mtce	Mtce	Ttce	Billion RMB	Million tonnes	Thousand tonnes
2000	Mean	183.83	21.67	34.98	10.68	1058.06	339.26	121.54	655.26
	Std. Dev.	176.53	15.66	23.88	11.58	1686.00	259.39	79.36	447.21
	Max	665.57	60.72	101.88	56.27	7803.11	1074.13	314.69	1795.90
	Min	13.54	2.39	1.37	0.56	1.33	26.37	8.44	20.40
2003	Mean	254.96	21.58	45.88	12.11	1569.36	447.82	155.64	719.48
	Std. Dev.	248.22	14.33	32.71	13.59	2069.80	357.82	102.43	464.19
	Max	879.46	55.36	146.45	65.15	9932.44	1531.53	413.66	1835.70
	Min	18.19	2.54	2.41	0.53	13.30	36.95	16.26	22.92
2006	Mean	409.14	23.85	71.22	16.40	2601.04	677.43	236.68	862.20
	Std. Dev.	376.26	16.78	55.75	17.64	2931.88	549.11	170.75	510.46
	Max	1287.01	64.12	213.14	79.36	14108.64	2292.95	714.08	1962.00
	Min	27.59	2.71	2.37	1.49	75.81	52.23	18.50	24.00
2009	Mean	623.27	24.93	83.61	19.86	4293.40	937.56	292.57	737.93
	Std. Dev.	556.84	16.62	61.25	20.16	4089.44	759.55	186.14	420.57
	Max	1975.77	59.49	248.54	83.90	16889.67	3185.17	796.91	1590.00
	Min	41.39	2.85	3.83	1.17	160.93	73.43	30.31	22.00

(a) Mtce and Ttce: million and thousand tonnes of coal equivalent, respectively.

Table 2 China's areas and regions and the related data

Areas	**Regions (provinces, autonomous regions, and municipalities) included**	**Year**	**Total GDP(RMB Billion)**	**Total energy consumption(Mtce)**	**Total CO_2 emissions(Mt)**
East area	Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Hainan;	2000	5741.19	656.34	1682.71
		2005	10334.51	1122.14	2902.74
		2009	16728.18	1475.21	3782.65
Central	Shanxi, Jilin, Heilongjiang, Anhui,	2000	2400.37	439.37	1166.30

area	Jiangxi, Henan, Hubei, Hunan;	2005	4035.71	734.32	1969.93
		2009	6569.88	915.60	2452.92
West area	Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang.	2000	1697.08	305.92	797.08
		2005	2903.48	563.65	1471.81
		2009	4828.78	842.34	2160.00
Whole country	30 regions	2000	9838.63	1401.63	3646.09
		2005	17273.71	2420.10	6344.49
		2009	28126.84	3233.16	8395.57

(a)Mtce:million tonnes of coal equivalent,Mt:million tones.

As shown in Table 2, the east area comprises8 coastal provinces and 3 municipalities. This area has experienced the most rapid economic growth during the past 30 years.Itstotal yearly GDP output is closeto 60%of China's total GDP output and its energy consumption takes up to morethan 45% of China's total energy consumption.The central area consists of 8 regions which are all inland provinces. The GDP output of this area is less than that of the east area but more than that of the west area. The percentages of GDP and energy consumption of central area are around 25% and 30% of the whole country, respectively.The west area includes 1 municipality, 2 autonomous regions and 10 middle-west provinces, which covers more than half of the territory of China. This area produces about 15% GDP outputs, however, consumes about 25% of the energy of the whole country.

4 Comparative analyses of China's regional energy and emission performance

4.1 Operationalizing the methods

In order to make comparative analyses of the energy and emission performance based on different undesirable outputs treatment methods, as well as to comprehensively analyze the energy performance and the unified energy and emission performance, we operate three DEA models combined with the applicationof DEA window analysis and the K-W rank sum test in this section.

Firstly, we use Model (1), but remove the forth constraint to ignore the undesirable outputs, i.e., the emission variables of CO_2 and SO_2 are excluded from the model, to calculate the simplex Energy Performance Indicator (*EPI'*) for each region. Secondly, Model (2) and (3) are utilized to calculate the Unified Energy and Emission Performance Indicators ($UEEPI_1$ and$UEEPI_2$) when the undesirable emission outputs are treated as inputs and transformed to be similar to desirable outputs, respectively. We emphasize that the window analysis technique is applied throughoutthe computation process of Model (1) to Model (3). Finally, we use the K-W rank sum test to examine the data validity of 90 observations in each window. Since all the multiple observations in each statistical test have ties, we calculate statistic H^c using the adjusted equation (5). The results of the rank sum test shows that all$H$ scores are less than 5.991, which is the critical value of the χ^2 distribution at the 5% significance under the degree of freedom 2. Thus we can confirm the validity of the three years' data aggregation in a window.

The unified energy and emission performance indicators $UEEPI_1$and $UEEPI_2$ of 30 China's regions are presented in Table 3. The mean valueof each performance indicatorfor each region,area,and the whole country of China during the period of 2000 to 2009are also calculated and shown in Table 3.

Table 3 Energy and emission performance of China's30 regions under different models

Region\Year		$UEEPI_1$(undesirable outputs as inputs)					$UEEPI_2$ (undesirable outputs transformed)				
		2000	2003	2006	2009	Mean	2000	2003	2006	2009	Mean
East area	Beijing	0.9092	1	0.9921	1	0.9878	0.9801	1	0.9909	1	0.9933
	Tianjin	1	1	1	1	0.9958	1	1	1	1	0.9970
	Hebei	0.3785	0.9357	1	1	0.8553	0.4121	0.4637	0.7211	0.5200	0.5203
	Liaoning	1	1	1	1	0.9985	1	1	1	1	0.9940
	Shanghai	1	1	0.9834	1	0.9977	1	1	0.9633	1	0.9951
	Jiangsu	1	1	0.9640	1	0.9811	1	0.9387	0.7699	1	0.8715
	Zhejiang	0.6036	0.9446	0.9526	1	0.9179	0.7816	0.7969	0.8395	1	0.8872
	Fujian	1	1	1	1	1	1	1	1	1	1
	Shandong	1	1	1	1	0.9557	1	1	1	1	0.9441
	Guangdong	0.8725	1	1	1	0.9872	0.8836	1	1	1	0.9884
	Hainan	1	1	1	1	1	1	1	1	1	1
	Mean	0.8876	0.9891	0.9902	1	0.9706	0.9143	0.9272	0.9350	0.9564	0.9264
Central area	Shanxi	0.4131	1	1	1	0.8888	0.8007	0.8719	0.7175	0.3829	0.7441
	Jilin	0.5406	1	0.9837	1	0.9355	0.9364	1	0.9635	1	0.9791
	Heilongjiang	1	0.9945	0.9788	1	0.9837	1	0.9834	0.9216	1	0.9685
	Anhui	1	1	1	1	0.9947	1	1	0.9925	1	0.9859
	Jiangxi	1	1	0.9438	0.9497	0.9771	1	1	0.9256	0.9385	0.9738
	Henan	0.4825	1	1	1	0.8971	0.5050	1	0.8634	0.7597	0.7561
	Hubei	0.3929	0.8956	0.8441	0.8668	0.7802	0.6872	0.6839	0.6268	0.6906	0.6691
	Hunan	0.7648	0.9238	0.8605	0.9295	0.8770	1	0.8116	0.7077	0.8077	0.8256
	Mean	0.6992	0.9767	0.9514	0.9683	0.9168	0.8662	0.9189	0.8398	0.8224	0.8628
West area	Chongqing	0.4711	1	0.9652	1	0.8761	1	1	0.9550	1	0.9514
	Sichuan	1	1	1	1	1	1	1	1	1	1
	Guizhou	0.3301	0.9699	1	0.9158	0.8481	1	0.8781	1	0.8138	0.9211
	Yunnan	1	1	1	1	1	1	1	1	1	0.9992
	Shaanxi	0.3890	0.7620	0.7863	0.8162	0.7054	0.6190	0.5934	0.5851	0.5549	0.5850
	Gansu	0.5096	0.7871	0.8054	0.8315	0.7488	0.7071	0.6486	0.7187	0.7570	0.7056
	Qinghai	1	1	1	1	1	1	1	1	1	1
	Ningxia	1	0.8663	1	1	0.9783	1	0.8037	1	1	0.9804
	Xinjiang	0.2048	0.8188	0.7460	0.7698	0.6754	0.7186	0.6718	0.5874	0.5344	0.6382
	Guangxi	1	1	1	1	0.9988	1	1	1	1	0.9985
	Inner Mongolia	1	1	1	1	0.9741	1	1	0.8344	1	0.9739
	Mean	0.7186	0.9276	0.9366	0.9394	0.8914	0.9132	0.8723	0.8801	0.8782	0.8867
Whole country		0.7754	0.9633	0.9602	0.9693	0.9272	0.9272	0.9049	0.8895	0.8920	0.8949

From Table 3, we could find that: i) The performance of 4 regions (Fujian, Hainan, Sichuan and Qinghai) from 2000 to 2009 have always been the benchmarks for lying on the energy and emission efficiency frontier, under both Model (2) and (3); furthermore, there is one more region (Yunnan) is also lying on the efficient frontier under Model (2). ii) For most regions and for all three areas of China, themean values on $UEEPI_1$ fromModel (2) are higher than that on $UEEPI_2$ from Model (3) during the period of 2000 to 2009. iii) There are more efficient regions which have unity values on performance indicatorsunder Model (2) than Model (3).

4.2 Comparative analyses of performance under different undesirable outputs treatments

In order to make a clearer comparative analysis of the performance evaluation results from different models (under different undesirable outputs treatments), we first illustrate all the values of $UEEPI_1$ and $UEEPI_2$ for China's 30 regions from 2000 to 2009 in a scatter diagram (Figure 1).

i) There are more observations located below the diagonal(115 ones) than those located above it(38 ones), and the mean value of $UEEPI_1$ (0.927) are higher than that of $UEEPI_2$ (0.895) for all 300 observations (30 regions for 10 years). The Wilcoxon matched-pairs signed-ranks test (Daniel, 1978)is applied here for all of the observations. The testconfirms that the performance indicators measured by Model (2) are higher than those measured by Model (3),and the null hypothesis (the performance measure under Model (2) is the same as that under Model (3)) could be rejected at 1% level of significance. Therefore, we could conclude thatModel (2) may overestimate China's regional energy and emission performance compared with Model (3).

ii) The projections of the observations on the horizontalaxis are more concentrated than those on the vertical axis.We further calculate the values of coefficient of variation (CV)for$UEEPI_1$and $UEEPI_2$ which are 0.147and 0.173, respectively. This resultindicates that totreat the undesirable outputs as inputs under Model (2) has weaker discriminating power thanto mathematicallytransformthe undesirable outputs into "desirable" outputsunder Model (3) in the evaluationof China's regional energy and emission performance.

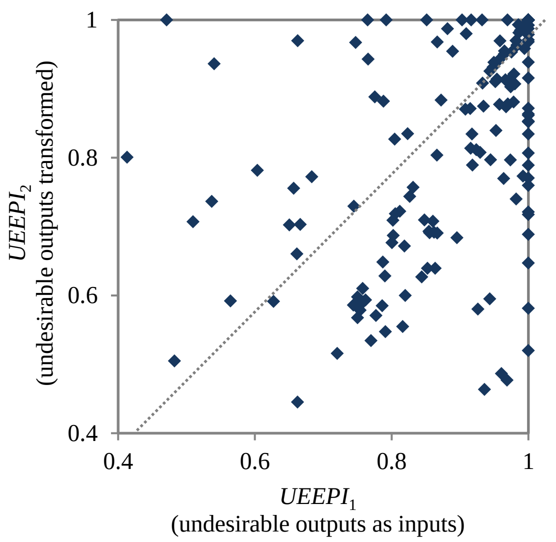

Figure 1 Comparison of performance indicatorsunder different undesirable outputs treatments

4.3 Comparative analyses of simplex energy performance and unified energy and emissionperformance

In this section, we further compare the simplex energy performance (without considering the outputs of CO_2 and SO_2 emissions) indicated by *EPI'* with the unified energy and emission performance (CO_2 and SO_2 emissions are included as undesirable outputs) indicated by $UEEPI_1$ and $UEEPI_2$ under different treatments of undesirable outputs in order to gain an insight into the relationship between these two kinds of performances for different regions of China. Combined with the analysis of China's regional economic and social development, this comparison could provide us with more information about the difference between the treatments of undesirable outputs in Model (2) and (3).

We illustrate the mean value of *EPI'* (denoted using the horizontal axis) associated with mean values of $UEEPI_1$ and $UEEPI_2$ (denoted using the vertical axis)of China's 30 regions during the period of 2000 to 2009 in two scatter diagrams (Figure 2).

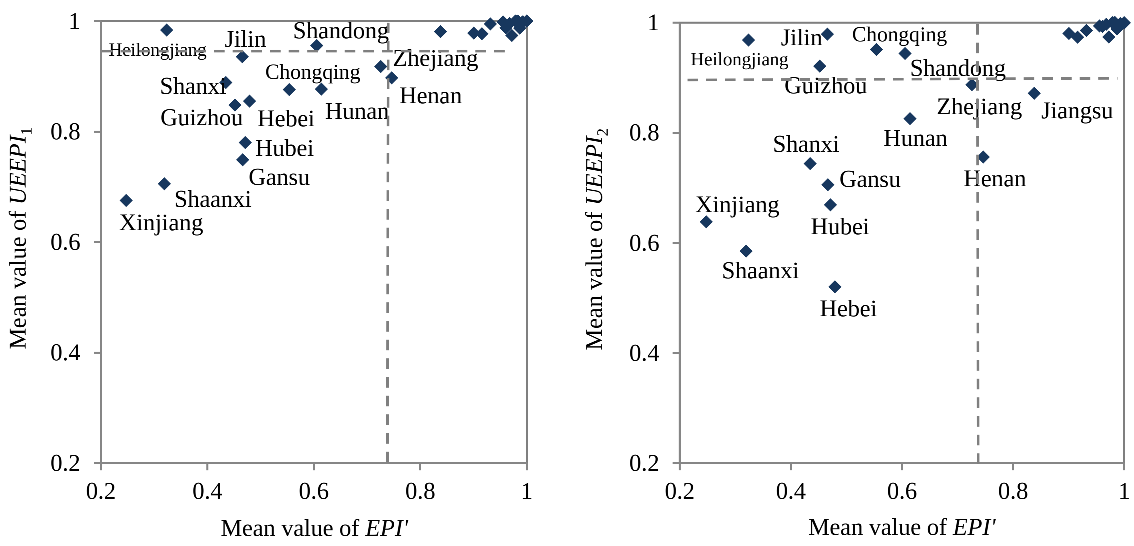

Figure 2 Simplex energy performance and unified energy and emission performancecomparison

For analytical convenience, wedivide each of the scatter diagrams in Figure 2 in to four quadrants according to the mean valueof each performance indicatorof these 30 regions. The northeast quadrant is distinguished by both high energy performance and high unified energy and emission performance. Conversely, the southwest quadrantsuffered both low energy performance and low unified energy and emission performance. The remaining two quadrants present only one high performance on energy utilization or pollutant emissions.

From Figure 2we could find that:i) Theobservations distribute more concentrated in the left-handscatter diagramwhich compares$UEEPI_1$ with*EPI'*,and there are more observationslocate close to the diagonal of the right-handscatter diagramwhich comparing $UEEPI_2$ with *EPI'*. ii) The projections of 30 observations on verticalaxis for $UEEPI_1$are more concentrated than those for $UEEPI_2$, and the coefficient of variation on the mean values of $UEEPI_1$ (0.102) is lower than that of $UEEPI_2$ (0.160). Thesephenomenaindicate that on the one hand, the treatment of undesirable outputs transformationhas strongerdiscriminating power in the evaluation of China's regional energy and emission performance. On the other hand, however, the treatment of undesirable outputs as inputs gives more information on the differences between simplexenergy performance and unified energy and emission performance. The distribution of the observations (located beyond the diagonals in twoscatter diagrams of Figure 2) indicates that the simplex energy performance evaluated under Model (1) (excluding the undesirable outputs) is a "biased estimation" compared with the unified energy and emission performance evaluated under Model (2) and (3), and the treatment of undesirable outputs as inputsunder Model (2) can detect this "bias" more effectively.

According to the classifications shown in Figure 2, China's 30 regions can be grouped into four quadrants, which are also summarized in Table 4 and 5. It can be seen that the regions have the same classifications under the two undesirable outputs treatments, apart from3 regions. Jiangsu is classified in the high simplex energy performance and high unified energy and emission performance quadrant(i.e., the High-High quadrant) under Model (2), but is then grouped into the high simplex energy performance and low unified energy and emission performancequadrant (i.e., the High-Low quadrant) under Model (3).Furthermore, in the low simplex energy performance quadrant, 2 regions (Chongqingand Guizhou) have contradicting classificationsin terms of the unified energy and emission performance.AsJiangsu is one of the major industrial bases in east China, its total energy consumption and total CO_2emissionsarequite large and ranked in the top 4 in China.Therefore, it will be more reasonable to characterizeJiangsu as a high simplex energy performance but low unified energy and emission performance region.In addition, although the economic development level of Guizhouisrelatively low inwest China, its energy consumption and CO_2emissionsare also at low levels compared with other regions. Therefore, to classify Guizhou in the low simplex energy performance but high unified energyand emission performance quadrant is considered to be more acceptable.

Table 4 Classification of performances from Model (2)

Undesirable outputs as inputs		Unified energy and emission performance	
		Low (11 region)	High (19 regions)
Simplex energy performance	High (17 regions)	Henan (1 region)	Beijing, Tianjin, Inner Mongolia, Liaoning, Shanghai, Jiangsu, Anhui, Fujian, Jiangxi, Guangdong, Guangxi, Hainan, Sichuan, Yunnan, Qinghai, Ningxia (16 regions)
	Low (13 regions)	Hebei, Shanxi, Zhejiang, Hubei, Hunan, Chongqing, Guizhou, Shaanxi, Gansu, Xinjiang (10 regions)	Jilin, Heilongjiang, Shandong (3 regions)

Table 5 Classification of performances from Model (3)

Undesirable outputs transformed		**Unified energy and emission performance**	
		Low (10 regions)	High (20 regions)
Simplex energy performanc	High (17 regions)	Jiangsu, Henan (2 regions)	Beijing, Tianjin, Inner Mongolia, Liaoning, Shanghai, Anhui, Fujian, Jiangxi, Guangdong, Guangxi, Hainan, Sichuan, Yunnan, Qinghai,

e			Ningxia (15 regions)
	Low (13 regions)	Hebei, Shanxi, Zhejiang, Hubei, Hunan, Shaanxi, Gansu, Xinjiang (8 regions)	Jilin, Heilongjiang, Shandong, Chongqing, Guizhou (5 regions)

4.4 Discussions on the performance evaluation results

Since these two undesirable outputs treatments under Model (2) and (3) both have their own advantages and disadvantages from different evaluation perspectives, it will be truly difficult, in general, to say which way to deal with the undesirable outputs is better. However, as compared and discussed above in Section 4.2 and 4.3, because i) $UEEPI_2$has stronger discriminating power than $UEEPI_1$, ii) the utilization of $UEEPI_2$ can avoid the performance overestimation,and iii) Model (3) can provide more reasonable performance evaluation results that reflectthe characteristics ofChina's regions, the treatment of undesirable outputs transformation under Model (3) dominates the treatment of undesirable outputs as inputs under Model (2) and the associated indicator of $UEEPI_2$ is more appropriate than $UEEPI_1$ in the unified energy and emission performance evaluation for China's regions.Therefore, further discussions on performance evaluation results in this section will be based on Model (3) and $UEEPI_2$.

First, we illustrate meanvalues of $UEEPI_2$for the 30regions of Chinaover the ten-yearperiod (2000-2009) in Figure 3.All of the regions are clustered into three groups of high performance ($UEEPI_2 \geq 0.99$), medium performance ($0.85 \leq UEEPI_2 < 0.99$) and low performance ($UEEPI_2 < 0.85$). i) In the east area, sixregions (Beijing, Tianjin, Liaoning, Shanghai, Fujianand Hainan) exhibit high performance;fourregions (Jiangsu, Zhenjiang, Shandong and Guangdong) havemedium performance;andonly one region(Hebei)is assign to the low performance group.ii) In the central area, no region has high performance;Jilin, Heilongjiang, Anhui and Jiangxi are in medium performance group;the remaining regions of Shanxi, Henan, Hubei and Hunanexhibit low performance.iii) In the west area, four regions of Sichuan, Yunnan, Qinghai and Guangxi are in the high performance group; another four regions of Chongqing, Guizhou, Ningxia and Inner Mongolia are in the medium performance group; the remaining three regions (Shaanxi, Gansu and Xinjiang) are in the low performance group. iv) Ingeneral, the east area outperforms the west area and the centralarea performs worst.

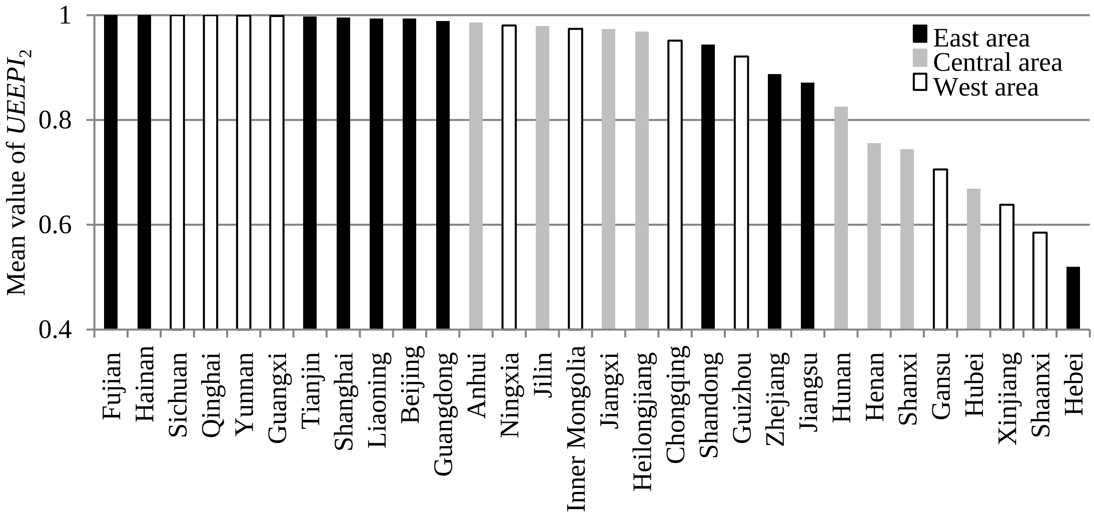

Figure 3 China's regional unified energy and emission performance (2000-2009)

We also calculate the mean values of $UEEPI_2$of China as a whole and its three areas for each year from 2000 to 2009.The time trend for each of these values is shown in Figure 4. This figure indicates that: i) from the area perspective, the east area exhibitsthe highest average unified energy and emission performance for almost all years during our study period, and the central area has the lowest average performance for 7 years (2000-2001 and 2005-2009). The performance of the west area fluctuatesbetween that of the east and central area for 7 out of 10 yearsduring our study period (the exceptionsbeing2002-2004). ii) The east andwest area have approximately opposite increasing and decreasing trendson their performances, and the performance of the central area fluctuated greatlyover the study period. iii) The unified energy and emission performance of China remained stable around 0.90 for the first 4 years from 2000 to 2003 and then decreased slightly to 0.88 in 2007. After this, China's performance continuedto increaseuntil 2009. iv)Theperformance gap between theeast and central areas widened after 2003, since the east area experienced a continuous performance increase in 2005-2006 and 2007-2009; however, the performance of the central area decreased significantly from 2003 to 2005 andremained at a low level for 5 years until 2009.

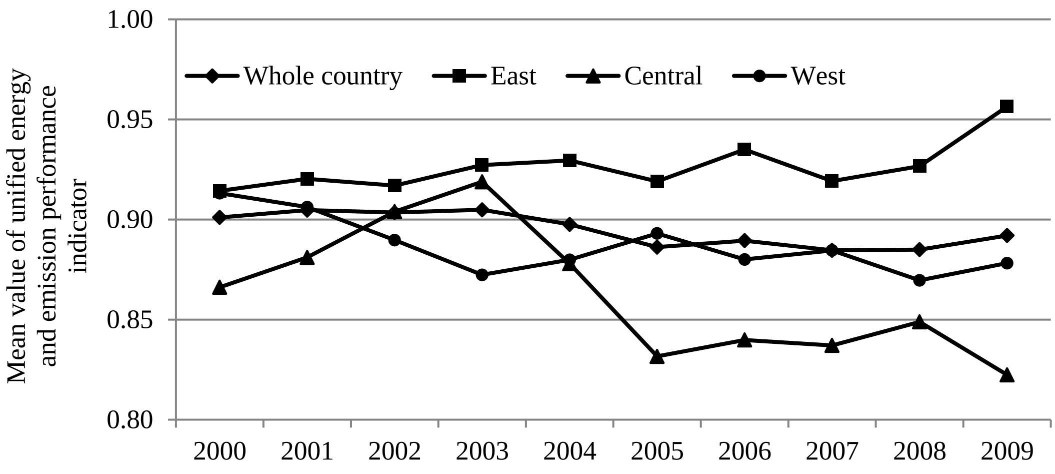

Figure 4 Time trend ofenergy and emission performance (2000-2009)

In order to dynamically analyze the performance changes for each region during our study period and give a more detailed and clear demonstration, we illustrate 30 regions' unified energy and emission performance in 2000, 2003, 2006 and 2009 in Figure 5. It could be seen that: i) The performances of 6 regions increased from 2000 through 2003 and 2006 until 2009, and the most evident increases appeared intwo east China regions of Zhejiang and Hebei whose performances increased about 20%. ii) The performances of another 6 regions decreased during the same period, and the most evident decreases appeared in twocentralChina regions of Shanxi and Hunan whose performance decreased about 40% and 20%, respectively. iii)Thereare 7 regions experienced a performance fluctuating process during the study period, and the most significant fluctuation appears in Henan, whose coefficient of variation on performance is above 0.21.iv)The performances of the remaining 11 regions kept approximately stable at high levels during our study period.

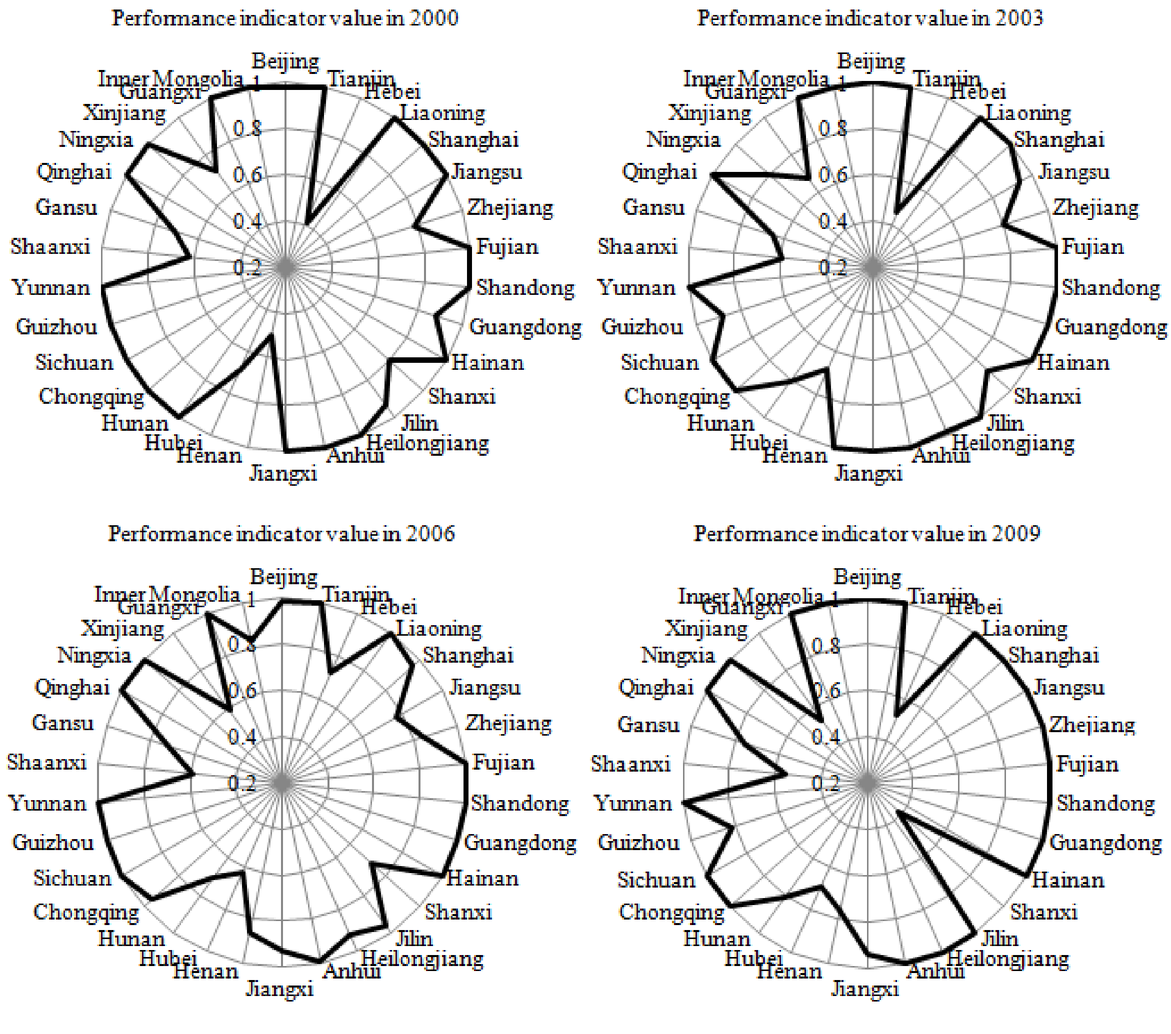

Figure 5 Unified energy and emission performanceindicator value of 30 regions

Figure 6compares the average energy and emission performance of 30 regions in the east, central and west area of China, which are grouped and shown in the east part, southwest part and northwest part of the radar chart, respectively.We could find that: i) East China regions exhibit a more balanced performance than the regions in central and west China, except Hebei who suffered a relative low energy and emission performance. ii) In central China, Anhui and Jiangxi perform best butShanxiand Henan perform worst, and together with Hunan and Henan, these 4worst performing regions lead to the lowest performance indicator value of the central area in the whole country. iv) Since Sichuan, Qinghai, Yunnan and Guangxi perform verywell in west China, Shaanxi and Xinjiang sufferquite low performance which is just a little above Hebei's performance level.

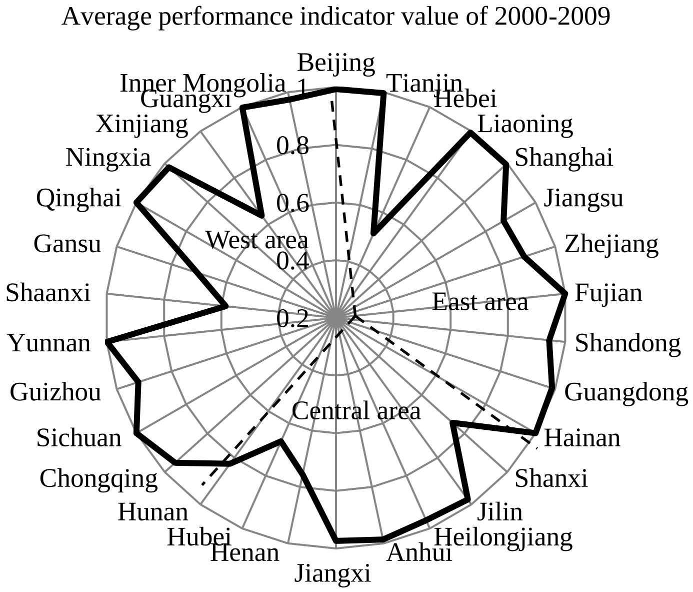

Figure 6 Average energy and emissionperformance index of 30 regions

In order to give an extended analysis to the relationship between the energy utilization, economic development, pollutant emissions and environmentprotection in this paper, we return to the analysis of Figure 2 and Table 5,in which the correlation between the unified energy and emission performance (*UEEPI*$_2$) and simplex energy performance (*EPI'*) are applied to classify the observations.

The classifications of the observations show thatfifteen out of thirty regions areassigned into the "High-High" group, which is characterized by both high energy performance and high emission performance. About two-thirds east China regions and more than one-half west China regions are located in this group, whichimplies thatthe major part of the east and west China enjoys a highenergy utilizationefficiency whether considering pollutant emissions or not.

On the contrary, eight out of thirty regions areassigned into the "Low-Low" group, which is characterized by both low energy performance and low unified energy and emission performance. About one-half of the regions in central China are located in this group, which implies that the major part of central China suffers both a lowenergy utilization efficiency and a low emission efficiency. Regions of this group are recommended to take the regions in "High-High" group as benchmarksfor further improvement of energy and emission performance.

There are five regions, one from east China, two from central China and another two from west China, locate in the "Low-High" group, which exhibitbad on energy performance but good on emission performance. Regions in this group suffer a low energy utilization efficiency,however, they perform better on the emissionsreduction compared with the regions in the “Low-Low” group. Regions of this group are recommended to keep their emissions stable and improve their energy utilization through technology and management innovation.

Furthermore, the remaining two regionsare classified in the “High-Low” group, which perform well on energy utilization efficiency but are evaluated with low emission efficiency when considering the pollutant emission factors. Regions in this group need to pay more attention on the reduction of CO_2 and SO_2 emissions,and the total energy consumption control to further improve their energy and emission performance.

5 Conclusion

Within a joint production framework of desirable output and undesirable emission outputs, as well as separated energy inputs and non-energy inputs, this study proposedseveral data envelopment analysis based modelsand three performance indicators to evaluate the total-factor energy and emission performances of 30 administrative regions and three areas of China. In addition, the DEA window analysis technique was applied to deal with cross-sectional and time-varying data, so as to dynamically evaluate the performance during the study period of 2000 to 2009. Two different undesirable outputs treatments are combinedin our DEA models and the corresponding evaluation results on simplex energy performance indicator and unified energy and emission performance indicators are systematically compared in order to give a comprehensive analysis of the characteristics of these two undesirable outputs treatments.

The comparative analysis of this study indicates that,on the one hand, to treat the transformed emission outputs as “desirable” outputs has stronger discriminating power in the China’s regional energy and emission performance evaluation, and to treat the emission outputs as inputsmay overestimate the performance. However, on the other hand, to treat the transformed emission outputs as desirable outputs can provide more information on the differences between energy performance and emission performance, since this treatment could effectively detect the “bias” of the simplex energy performance evaluation compared with the unified energy and emission performance evaluation.Furthermore, the treatment of undesirable outputs transformation can provide more reasonable and acceptable evaluations results that reflect the characters of China’s regions.Therefore, we point out that, forChina’s regional energy and emission performance evaluation, the treatment of undesirable outputs transformation and the associate DEA method is more appropriate than the treatment of undesirable outputs as inputs and the associated DEA method.

The empirical study resultsof this paper shows that,on average, the unified energy and emission performance of the east China is best, while that of the central China is worst,and the gap between the performances of these two areas becomes larger since 2003 . Compared with the central and west area, regions in east China enjoyeda more balanced energy and emission performance during our study period. Most east China regions are classified into the “High-High”performance group, which exhibit not only high simplex energyperformance but high unified energy and emission performance. However, about half of central China regions are classified into the “Low-Low”performance group and they sufferedfrom both lowenergy utilizationefficiency andlow pollutant emissionefficiency. As a whole country, China’s unified energy and emission performance appeared stable during 2000-2003, slightly decreased from2004 to 2006, and kept on increasing since 2007.

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