Nonradial Directional Distance Function for Measuring the Environmental Efficiency of the Chinese Iron and Steel Industry

Authors: Zhou, Zhixiang, Wu, Huaqing, Ding, Tao, and Xia, Qiong

Source: Tropical Conservation Science, 12(1)

Published By: SAGE Publishing

URL: https://doi.org/10.1177/1940082919853755

Tropical Conservation Science
Volume 12: 1–12

DOI: 10.1177/1940082919853755
journals.sagepub.com/home/trc
SAGE

Nonradial Directional Distance Function for Measuring the Environmental Efficiency of the Chinese Iron and Steel Industry

Zhixiang Zhou[1], Huaqing Wu[1], Tao Ding[1] and Qiong Xia[1]

Abstract

The present article constructs nonradial directional distance function (DDF) methods to measure and contribute to improving the industrial sustainability performance of the Chinese iron and steel industry. For such an energy-intensive industry, environmental efficiency measurement is an important way to implement the "energy-saving and emission-reduction" principle. We reformulate the nonradial DDF in the form of Second-Order Cone Programming in order to transform the traditional DDF into linear programming and provide accurate efficiency results. The new approach is utilized to calculate the performance of 30 major iron and steel makers in China. Both technical efficiency and overall efficiency are calculated to help the managers of inefficient iron and steelmakers find weaknesses. We find that nearly half of the steel makers are environmental inefficient, most of which are increasing return to scale. Furthermore, specific value of desirable output increase and undesirable output reduction are calculated for achieving efficiency. The study concludes with some remarks for energy-environment policy and industrial decision makers based on the empirical analysis and makes comparison study between the policies obtained in this study and the existing government policies.

Keywords

data envelopment analysis, environmental efficiency, directional distance function, industrial sustainability, iron and steel industry

Introduction

After high-speed development in recent decades, China's manufacturing industry has gained a remarkable increase and is consuming a huge amount of material. Manufacturing has also promoted the development of many industries in China, particularly the iron and steel industry. The production of crude steel in China has increased from 128.5 billion tons in 2000 to 803.8 billion tons in 2015, which accounts for 49.6% of world production. To sustain such a large production, the Chinese iron and steel industry consumes huge amounts of energy and iron ore and also emits a great deal of pollution. As shown in the report of the China Iron and Steel Association (2011), the iron and steel industry places a heavy burden on the environment, releasing about 14% of the national waste water and waste gas, and about 7% of the national waste solid materials. The improvement of industrial energy efficiency is accordingly identified as a key element to reduce the threat of increased pollution problems such as global warming (International Energy Agency, 2011), and increasing researches have been done on energy management practices in iron and steel industry (Brunke, Johansson, & Thollander, 2014).

As a major pollution resource among all the manufacturing industries in China (He, Zhang, Lei, Fu, & Xu, 2013), Chinese government has recognized the environmental problems caused by iron and steel industry. For the existing iron and steel plants, achieving higher environmental efficiency by increasing the production of iron and steel while decreasing pollution

[1]School of Economics, Hefei University of Technology, P.R. China

Received 6 November 2018; Revised 29 April 2019; Accepted 3 May 2019

Corresponding Author:
Tao Ding, School of Economics, Hefei University of Technology, 193, Tunxi Road, Hefei 230009, Anhui, P.R. China.
Email: hfutdingtao@126.com

emission is the only practical choice which will also meet the demand of industrial sustainable development. Singh, Murty, Gupta, and Dikshit (2007) develop composite sustainability performance index and use analytical hierarchy process to calculate the performance of major steel companies in India. Lin and Wang (2014) evaluate the energy efficiency of iron and steel industry in China's regions during 2005 to 2011 by using the excessive energy-input stochastic frontier model. Cost-efficiency energy conservation measures is utilized by Brunke et al. (2014) to calculate the performance of Swedish iron and steel industry. The bottom-up model is considered as a feasible way to analyze the performance of China's iron and steel industrial energy consumption and CO_2 emission and estimate the efficiency improvement and emission reduction potentials (W. Chen, Yin, & Ma, 2014; Hasanbeigi, Morrow, Sathaye, Masanet, & Xu, 2013). Moreover, many other approaches such as energy conservation supply curves (S. Zhang, Worrell, Crijns-Graus, Wagner, & Cofala, 2014) and vector autoregression model (Xu & Lin, 2016) are also used to calculate the efficiency and improvement potential of China's steel and iron industry.

As a popular nonparameter tool, data envelopment analysis (DEA) approach (Charnes et al., 1978) is widely used to measure the performance of steel and iron sector. Ma, Evans, Fuller, and Stewart (2002) utilize DEA approach to calculate the environmental efficiency of 88 enterprises in China's iron and steel industry during 1989 to 1997. He et al. (2013) compose the Malmquist–Luenberger Productivity index based on DEA to measure the performance of 50 enterprises in China's iron and steel industry during 2006 to 2008 and find that the average efficiency score was only 61.1%. Wei, Liao, and Fan (2007) use DEA-based Malmquist index to measure the energy efficiency of iron and steel sector in different Chinese regions by using the provincial panel data during the period 1994 to 2003. Mitra Debnath and Sebastian (2014) and Morfeldt and Silveira (2014) focus the efficiency of iron and steel sectors in India and Europe and utilize DEA approach to calculate the performance. Comparing with the parameter approach, DEA model can be used to calculate the efficiency of Decision Making Units (DMUs) based on multiple inputs and outputs without any information between the variables. However, most of these existing studies do not considered the negative effects of steel and iron industry to environment.

As a typical industry, the production process of steel and iron inevitably produce some bad output (undesirable output) such as waste water, waste gas, and waste solid. In the present, increasing researches have been done to calculate the environmental efficiency of industry with considering the inevitable pollution produced during the process of production (Song, Wang, Zhao, Baležentis, & Shen, 2018; Wu, Shi, Xia, & Zhu, 2014). The key problem for environmental efficiency calculation is to evaluate the undesirable output under DEA approach (Zhou, Guo, Wu, & Yu, 2018). Different from the classic method for evaluating the efficiency of iron and steel industry mentioned in the last paragraph, DEA basic models for environmental efficiency evaluation need to consider two kinds of outputs, desirable outputs and undesirable outputs, because the production of desirable outputs (such as crude steel) inevitably creates undesirable output (such as waste water, gas, and solids). Directional distance function (DDF) proposed by Chambers, Chung, and Färe (1996) is considered as a common way to allow DEA to deal with undesirable output (J. Chen, Xu, Song, & Liu, 2018; Song, Chen, & An, 2018) and are widely used for calculating environmental efficiency (Chung, Färe, & Grosskopf, 1997, Picazo-Tadeo, Beltrán-Esteve, & Gómez-Limón, 2012). For providing more accurate efficiency results, Zhou, Ang, and Wang (2012) propose a nonradial DDF model for measuring the environmental efficiency in which the performance of desirable outputs and undesirable outputs are considered separately. Taking steel and iron industry for example, the managers should measure the performance of steel (desirable output) and pollution (undesirable output), respectively, and describe them by using different efficiency scores. However, the nonradial DDF proposed in their paper is a nonlinear programming problem which is difficult to compute (Wang, Chiu, & Chiu, 2017; N. Zhang & Choi, 2013), while the alternative optimal function for nonradial DDF used in the studies mentioned earlier can result in inaccurate optimal values for the program solution (Wang, Su, Zhou, & Chiu, 2016).

This article intends to use the Second-Order Cone Programming (SOCP), which has proved to be an effective way to reformulate nonlinear programming (Sueyoshi & Sekitani, 2007; Wu & Zhou, 2014), for transforming nonradial DDF into linear programming. That can be used to calculate the environmental efficiency scores of DMU of steel and iron sector in more effective and accurate way. Based on our nonradial DDF, the efficiency scores of desirable output and undesirable output are measured respectively. This can provide a guide for the policy makers about how to reduce the emissions of pollution by increasing the environmental efficiency of iron and steel industry while maintaining or increasing the present level of iron and steel products. The rest of the article is organized as follows. The methodology is constructed in section "Methods," while its application to a numerical example using real-life data of Chinese 30 major iron and steel makers is shown in section "Results." The conclusion and research prospects are given in section "Discussion."

Methods

Environmental Production Technology

Assume there are n DMUs. Any $DMU_j (j = 1,2, \ldots n)$ uses m inputs to produce s desirable outputs. The ith input and rth output of DMU_j are denoted as x_{ij} and y_{rj}. Then the production possibility set (PPS) of DMU_0 (subscript 0 indicates the DMU being evaluated) based on the constant return to scale (CRS) assumption is expressed as follows:

$$PPS = \left\{ \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{r0}, \lambda_j \ge 0 \right\} \quad (1)$$

From PPS Equation 1, we see that inactivity is always possible, while the finite amount of inputs should produce finite outputs not beyond the best production possibility combination. Following the idea in Fare et al. (1989), we assume β is a positive value and rewrite the PPS as:

$$PPS = \left\{ \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \sum_{j=1}^{n} \lambda_j y_{rj} = (1+\beta) y_{r0}, \lambda_j \ge 0 \right\} \quad (2)$$

PPS (Equation 2) is equivalent to PPS (Equation 1). However, undesirable outputs should be considered in PPS in environmental efficiency measurement. We define that the best DMU should maximize desirable output and minimize undesirable output. Denote the tth undesirable output of DMU_j as $y_{tb}, t = 1, \ldots, w$. Then, the PPS for any DMU_0 can be written as:

$$PPS = \left\{ \begin{array}{l} \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \sum_{j=1}^{n} \lambda_j y_{rj} = (1+\beta) y_{r0}, \\ \sum_{j=1}^{n} \lambda_j y_{tj}^{b} = \left(1-\beta^{b}\right) y_{t0}^{b}, \lambda_j \ge 0 \end{array} \right\} \quad (3)$$

PPS (Equation 3) expresses the PPS while considering undesirable output based on constant returns to scale in which the variable $0 \le \beta^b \le 1$ and $0 \le \beta$. It is important to point out that the desirable outputs and undesirable outputs are evaluated using different variables. Also, the PPS (Equation 4) based on the variable returns to scale (VRS) assumption is formulated as follows:

$$PPS = \left\{ \begin{array}{l} \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \sum_{j=1}^{n} \lambda_j y_{rj} = (1+\beta) y_{r0}, \\ \sum_{j=1}^{n} \lambda_j y_{tj}^{b} = \left(1-\beta^{b}\right) y_{t0}^{b}, \lambda_j \ge 0, \sum_{j=1}^{n} \lambda_j = 1 \end{array} \right\} \quad (4)$$

Nonradial DDF

Based on the definition of PPS (Equation 3), we can construct a nonradial DDF model similar to that in Zhou et al. (2012) based on CRS to measure the performance on undesirable outputs together with that of desirable outputs. Different from the radial DDF in Chung et al. (1997), the performance of undesirable and desirable outputs are each calculated in nonradial way.

$$\begin{array}{l} Min: \ \dfrac{1-\beta_0^b}{1+\beta_0} \\ \sum_{j=1}^{n} \lambda_j x_{ij} \le x_{i0}, \ i = 1, 2, \ldots, m. \\ \sum_{j=1}^{n} \lambda_j y_{rj} \ge (1+\beta_0) y_{r0}, \ r = 1, 2, \ldots, s. \\ \sum_{j=1}^{n} \lambda_j y_{tj}^{b} \le (1-\beta_0^b) y_{t0}^{b}, \ t = 1, 2, \ldots, w. \\ \beta_0 \ge 0, 1 \ge \beta_0^b \ge 0, \lambda_j \ge 0, j = 1, 2, \ldots, n \end{array} \quad (5)$$

In model (Equation 5), β_0 denotes an increase in desirable output and β_0^b denotes a decrease in undesirable output. The environmental efficiency of DMU_o is defined as the optimal value $\frac{1-\beta_0^{b*}}{1+\beta_0^*}$. A DMU_o is environmentally efficient if and only if $\beta_0^* = 0$ and $\beta_0^{b*} = 0$.

However, the aforementioned nonradial DDF model is a nonlinear program that is difficult to resolve by using existing software. Some researchers changed the optimal function into an additive formula like $\beta_0 + \beta_0^b$ to convert the nonradial DDF result to a linear program. Based on the optimal values obtained, they use a second step to calculate the environmental efficiency by $\frac{1-\beta_0^{b*}}{1+\beta_0^*}$. Unfortunately, the environmental efficiency score obtained in this way might not be the global optimum solution (Wang et al., 2016).

Nonradial DDF based on SOCP

As shown in the research of Sueyoshi and Sekitani (2007), a nonlinear programming solution can be transformed into a linear program in the form of SOCP (see Appendix). Model (Equation 5) can be formulated into an SOCP as follows:

$$\begin{aligned}
& Min:\ \psi_0 \\
& \sum_{j=1}^{n} \tau_j y_{tj}^{b} - y_{t0}^{b} + d_{tb} = 0,\ t = 1, 2, \ldots, w. \\
& \sum_{j=1}^{n} \tau_j x_{ij} - \delta_0 x_{i0} + d_{ix} = 0,\ i = 1, 2, \ldots, m. \\
& \psi_0 + d_0^{\psi} = 1 \\
& \delta_0 - d_0^{\delta} = 1 \\
& \left| \begin{matrix} \dfrac{\sum_{j=1}^{n} \tau_j y_{rj} - \psi_0}{2} \\ \sqrt{y_{r0}} \end{matrix} \right|_2 \le \frac{\sum_{j=1}^{n} \tau_j y_{rj} + \psi_0}{2} \\
& \tau_j, d_{tb}, d_{ix}, d_0^{\psi}, d_0^{\delta} \ge 0
\end{aligned} \tag{6}$$

Model (Equation 6) is a linear programming SOCP form in which four slacks d_{tb},d_{iX},d_0^{ψ},d_0^{δ} are used in the constraints for transform them into equation. The environmental efficiency of DMU_0 is ψ_0^*, and DMU_0 is CRS efficient if and only if $\psi_0^* = 1$. It is obvious that the aforementioned nonradial DDF model is constructed based on the CRS assumption in which the scale of DMUs is assumed to be unchanged. Also, we can construct the nonradial DDF based on the VRS assumption as follows:

$$\begin{aligned}
& Min:\ \theta_0 \\
& \sum_{j=1}^{n} \tau_j y_{tj}^{b} - y_{t0}^{b} + d_{tb} = 0,\ t = 1, 2, \ldots, w. \\
& \sum_{j=1}^{n} \tau_j x_{ij} - \delta_0 x_{i0} + d_{ix} = 0,\ i = 1, 2, \ldots, m. \\
& \sum_{j=1}^{n} \tau_j - \delta_0 = 0, j = 1, 2, \ldots, m. \\
& \theta_0 + d_0^{\theta} = 1 \\
& \delta_0 - d_0^{\delta} = 1 \\
& \left| \begin{matrix} \dfrac{\sum_{j=1}^{n} \tau_j y_{rj} - \theta_0}{2} \\ \sqrt{y_{r0}} \end{matrix} \right|_2 \le \frac{\sum_{j=1}^{n} \tau_j y_{rj} + \theta_0}{2} \\
& \tau_j, d_{tb}, d_{ix}, d_0^{\theta}, d_0^{\delta} \ge 0
\end{aligned} \tag{7}$$

As the transformation $\tau_j = \lambda_j \delta_0$ is used above, the additional constraint $\sum_{j=1}^{n} \tau_j - \delta_0 = 0$ is equivalent to $\sum_{j=1}^{n} \lambda_j = 1$. Based on model (Equation 7), the environmental efficiency of DMU_0 is θ_0^*, and it is VRS efficient if and only if $\theta_0^* = 1$.

Results

A Numerical Example

In this section, a simple example is constructed to illustrate the use of the new models. Assume there are five DMUs, each produces one desirable output and one undesirable output by using a single input. All data are illustrated in Table 1:

We calculate the efficiency of the five DMUs listed in Table 1 by using the traditional nonradial DDF and the model (Equation 6) based on SOCP, respectively. As mentioned earlier, the traditional way to calculate a nonradial DDF solution is to replace the $Min: \theta_0^* = \left(1 - \beta_0^{b*}\right)/\left(1 + \beta_0^*\right)$ by $Max: \beta_0^{b*} + \beta_0^*$. From the efficiency results shown in Table 1, we can find that the efficiency scores obtained by the two models are the same. This equivalence means that the objective function $Max: \beta_0^{b*} + \beta_0^*$ used in the traditional nonradial DDF solution is equal to the function for calculating the efficiency $Min: \theta_0^* = \left(1 - \beta_0^{b*}\right)/\left(1 + \beta_0^*\right)$ in some cases.

Next, we consider another numerical example with six DMUs and the data in Table 2.

In Table 2, an additional DMU F is considered. Then, we can find that a difference in the efficiency scores of DMU E calculated by the traditional and new presented models. By using the models in Zhou et al. (2012), DMU E attains a higher optimal objective value $\beta_0^{b*} + \beta_0^* = 0.8$, while the environmental efficiency score increases from 0.519 to 0.556. It is noteworthy that the increase of efficiency score is unreasonable because the PPS of DMUs in Table 1 is dominated by the set for DMUs in Table 2. That means the objective function $Min: \theta_0^* = \left(1 - \beta_0^{b*}\right)/\left(1 + \beta_0^*\right)$ for DMUs in Table 1 should be no smaller than that of Table 2. On the other hand, the new model (Equation 6) does maintain the consistency of computed results, based on which the efficiency score of DMU E is still 0.519. The aforementioned simple numerical examples illustrate the difference between our new model based on SOCP and the traditional approach; in the next section, we apply our approach to real-life data.

Empirical Study With Chinese Iron and Steel Industry Data

The Chinese iron and steel industry has grown remarkably in past 30 years; it is now the worldwide leader in the production of crude steel and it consumes about 15% of China's national total energy. At the same time, the Chinese iron and steel industry is one of the

Table 1. Numerical Example With Five DMUs.

DMU	A	B	C	D	E
Input	2	2	4	2	2
Desirable output	6	4	6	6	4
Undesirable output	7	7	7	9	9
Zhou et al. (2012)					
$Max: \beta_0^{b*} + \beta_0^*$	1	0.500	1	0.222	0.722
$Min: \theta_0^* = \left(1 - \beta_0^{b*}\right)/\left(1 + \beta_0^*\right)$	1	0.667	1	0.778	0.519
Model (Equation 6)	1	0.667	1	0.778	0.519

Note. DMU = Decision Making Unit.

Table 2. Numerical Example With Six DMUs.

DMU		A	B	C	D	E	F
Input		2	2	4	2	2	2
Desirable output		6	4	6	6	4	7.2
Undesirable output		7	7	7	9	9	9
Zhou et al. (2012)							
$Max: \beta_0^{b*} + \beta_0^*$	0	0.500	0	0.222	0.8	0	
$Min: \theta_0^* = \left(1 - \beta_0^{b*}\right)/\left(1 + \beta_0^*\right)$	1	0.667	1	0.778	0.556	1	
Model (Equation 6)		1	0.667	1	0.778	0.519	1

Note. DMU = Decision Making Unit

major emitters of waste water, waste gas, and waste solids. Following China's green development strategy and objective in the national "13th Five-Year Plan" (2016–2020), all the iron and steel makers need to shift their work from developing production to increasing environmental efficiency. In this section, we measure the environmental efficiency of 30 major steel makers in China using data for the year 2010.

Data and measures. In China, many small and medium size steel makers with heavy pollution have already merged or shut down in recent years. For this reason, we select a sample of 30 major steel makers which, combined, account for 51.3% of the national total crude steel production. All the data are gathered from China's Iron and Steel Industry Annual Report (2011) and the China Iron and Steel Statistics Annual Report (2011).

Three indicators are used to illustrate the inputs in the production process: (X_1) Labor: the total number of full-time employees, (X_2) Energy consumption: the tons of coal equivalent of energy consumed, and (X_3) Sintering iron ore consumption: the tons of main material consumed in production. Three desirable outputs are selected to show the outputs of every steel maker: (Y_1) pig iron production: the tons of primary iron production, (Y_2) crude iron production: the tons of primary steel production, and (Y_3) finished steel production: the tons of finished steel production. Three undesirable outputs are considered to analyze the environmental efficiency performance: (Y_1^b) waste water: the tons of waste water emitted, (Y_2^b) Waste gas: the tons of waste gas emitted, and (Y_3^b) waste solids: the tons of solid waste emitted. Descriptive statistics of the steel makers in the sample is shown in Table 3.

Environmental efficiency measurement. For evaluating the performance on energy utilization and pollution treatment for Chinese iron and steel industry, we use the new presented nonradial DDF models to calculate the environmental efficiency of selected iron and steel sectors. The environmental efficiency results for the 30 major iron and steel makers are listed in Table 4. The environmental efficiency scores were calculated using both CRS and VRS models, and the efficiency results for desirable and undesirable outputs are shown as β_0^* and β_0^{b*}, respectively. Based on CRS, more than half (17 of 30) of the steel makers are efficient based on nonradial DDF, while the others need to improve their performance by increasing desirable outputs or decreasing undesirable outputs. The scores of the inefficient steel makers show their space for performance improvement. Xinyu Iron & Steel, for example, gets an efficiency score of 0.942, which means it needs to improve its performance a

Table 3. Descriptive Statistics of 30 Major Chinese Iron and Steel Makers.

Measures	Unit	Mean	Maximum	Minimum	*SD*
(X_1) Labor	People	25,500	115,573	4,010	22,864
(X_2) Energy consumption	10 thousand tons	466	1,961	85	365
(X_3) Sintering iron ore consumption	10 thousand cubic m	1,055	2,796	112	634
(Y_1) Pig iron production	10 thousand tons	702	2,325	101	475
(Y_2) Crude iron production	10 thousand tons	718	2,646	145	510
(Y_3) Finished steel production	10 thousand tons	706	2,681	204	502
($Y^b{}_1$) Waste water	10 thousand cubic m	1,523	10,989	50	2,009
($Y^b{}_2$) Waste gas	10 thousand cubic m	14,880,423	79,380,471	1,665,363	15,075,029
($Y^b{}_3$) Waste solids	10 thousand tons	499	1694	96	447

Table 4. Environmental Efficiency Scores of 30 Chinese Steel and Iron Makers.

		CRS assumption				VRS assumption			
No.	Iron and steel maker	β_0^*	β_0^{b*}	Efficiency Score	Rank	β_0^*	β_0^{b*}	Efficiency Score	Rank
1	Shuicheng Iron & Steel	0	0.111	0.889	21	0	0.104	0.896	25
2	Tianjin Iron & Steel	0	0	1	1	0	0	1	1
3	Handan Iron & Steel	0	0	1	1	0	0	1	1
4	Xuanhua Iron & Steel	0	0	1	1	0	0	1	1
5	Chengde Iron & Steel	0	0	1	1	0	0	1	1
6	Baotou Iron & Steel	0.025	0.587	0.402	30	0	0.374	0.625	30
7	Ansteel	0	0	1	1	0	0	1	1
8	Panzhihua Iron & Steel	0	0.454	0.546	28	0	0.350	0.650	29
9	Lingyuan Iron & Steel	0	0.415	0.585	27	0	0.253	0.747	28
10	Tonghua Iron & Steel	0	0.083	0.917	20	0	0.030	0.970	24
11	Baoshan Iron & Steel	0	0	1	1	0	0	1	1
12	Xinjiang BaYi Steel	0	0	1	1	0	0	1	1
13	SGIS Songshan	0	0.211	0.789	25	0	0.188	0.811	26
14	Guangzhou Iron & Steel	0	0	1	1	0	0	1	1
15	Nanjing Iron & Steel	0	0	1	1	0	0	1	1
16	Hubei Xinyegang Steel	0	0.189	0.811	23	0	0	1	1
17	Huaigang Special Steel	0	0	1	1	0	0	1	1
18	Xinyu Iron & Steel	0.062	0	0.942	19	0	0	1	1
19	Jiangxi PinXiang Steel	0	0	1	1	0	0	1	1
20	Sanming Steel	0	0	1	1	0	0	1	1
21	Jinan Steel	0.181	0.022	0.828	22	0	0	1	1
22	Laiwu Steel	0	0	1	1	0	0	1	1
23	Qingdao Iron & Steel	0	0.205	0.795	24	0	0.009	0.991	23
24	Anyang Iron & Steel	0.006	0	0.994	18	0	0	1	1
25	Henan Jiyuan Iron & Steel	0	0	1	1	0	0	1	1
26	Wuhan Iron & Steel	0.014	0.536	0.458	29	0	0	1	1
27	Echeng Iron & Steel	0	0	1	1	0	0	1	1
28	Liuzhou Iron & Steel	0	0	1	1	0	0	1	1
29	Xiangtan Iron & Steel	0	0	1	1	0	0	1	1
30	Lianyuan Steel	0	0.238	0.762	26	0	0.230	0.769	27

Note. CRS = constant return to scale; VRS = variable returns to scale.

relatively small amount to become efficient. In contrast, for some DMUs, such as Baotou Iron & Steel, the managers need to do much work regarding both desirable and undesirable outputs; Baotou's environmental efficiency score of only 0.402 means it needs to increase its performance by 59.8% to become efficient. The technical efficiency results calculated by the VRS-based approach are shown in the last three columns of Table 4. We can find that most of the DMUs (22 in 30) are technically efficient, with only eight steel makers are technically inefficient. When we look at the results using the CRS approach, we find that the condition for inefficient DMUs is different. Wuhan Iron & Steel, for example, obtains an efficiency score of 0.458 based on CRS, while it is efficient based on VRS. It is clear that Wuhan Iron & Steel performed very well in technical efficiency, but it needs to change its scale efficiency to become efficient.

The efficiency results for desirable and undesirable outputs were determined by the new nonradial DDF method and are shown as β_0^* and β_0^{b*} in Table 4. Based on the efficiency results of the CRS model, the inefficient DMUs can be divided into three categories corresponding to their performance on desirable and undesirable outputs. Some inefficient steel makers perform poorly regarding desirable output, such as Xinyu Iron & Steel and Anyang Iron & Steel; they need to improve their desirable outputs by a proportion of β_0^* while maintaining their undesirable outputs. Some other iron and steel makers, such as Panzhihua Iron & Steel and Lingyuan Iron & Steel, need to decrease their undesirable outputs by β_0^{b*} with the present level of desirable output production. The others, such Baotou Iron & Steel and Jinan Iron & Steel, need to both increase desirable outputs and decrease undesirable outputs to achieve optimal performance improvement. Based on the VRS model, we can find that all the inefficient DMUs only need to decrease undesirable outputs to become efficient, which means that all the DMUs are technically efficient regarding desirable outputs.

Moreover, we can calculate the type of returns to scale by comparing the efficiency scores obtained based on CRS and VRS. From the last column of Table 5, we can find that all the iron and steel makers can be divided into three classes based on having Increasing Returns to Scale (IRS), Decreasing Returns to Scale (DRS), and Constant Returns to Scale (CRS). All the iron and steel makers which are efficient based on the CRS approach must be optimal in both technical and scale efficiency, and they have the CRS property. In our application study, all the inefficient DMUs perform poorly in scale efficiency and need to change their scale. Two steel makers, namely,

Table 5. Efficiency Results and Type of RTS of 30 Chinese Steel and Iron Makers.

No.	Iron and steel maker	CRS efficiency score	VRS efficiency score	Type of RTS
1	Shuicheng Iron & Steel	0.889	0.896	DRS
2	Tianjin Iron & Steel	1	1	CRS
3	Handan Iron & Steel	1	1	CRS
4	Xuanhua Iron & Steel	1	1	CRS
5	Chengde Iron & Steel	1	1	CRS
6	Baotou Iron & Steel	0.402	0.625	IRS
7	Ansteel	1	1	CRS
8	Panzhihua Iron & Steel	0.546	0.650	IRS
9	Lingyuan Iron & Steel	0.585	0.747	IRS
10	Tonghua Iron & Steel	0.917	0.970	IRS
11	Baoshan Iron & Steel	1	1	CRS
12	Xinjiang BaYi Steel	1	1	CRS
13	SGIS Songshan	0.789	0.811	IRS
14	Guangzhou Iron & Steel	1	1	CRS
15	Nanjing Iron & Steel	1	1	CRS
16	Hubei Xinyegang Steel	0.811	1	DRS
17	Huaigang Special Steel	1	1	CRS
18	Xinyu Iron & Steel	0.942	1	IRS
19	Jiangxi PinXiang Steel	1	1	CRS
20	Sanming Steel	1	1	CRS
21	Jinan Steel	0.828	1	IRS
22	Laiwu Steel	1	1	CRS
23	Qingdao Iron & Steel	0.795	0.991	DRS
24	Anyang Iron & Steel	0.994	1	IRS
25	Henan Jiyuan Iron & Steel	1	1	CRS
26	Wuhan Iron & Steel	0.458	1	IRS
27	Echeng Iron & Steel	1	1	CRS
28	Liuzhou Iron & Steel	1	1	CRS
29	Xiangtan Iron & Steel	1	1	CRS
30	Lianyuan Steel	0.762	0.769	IRS

Note. CRS = constant return to scale; VRS = variable returns to scale; IRS = Increasing Returns to Scale; RTC= Return to Scale.

Table 6. Improvement Target Values for Inefficient Steel Makers Based on CRS Model.

		Desirable output			Undesirable output		
No.	Iron and steel maker	Pig iron production	Crude iron production	Finished steel production	Waste water	Waste solids	Waste gas
1	Shuicheng Iron & Steel	325	328	321	286	351	3,521,932
6	Baotou Iron & Steel	995	1,037	978	394	779	10,449,413
8	Panzhihua Iron & Steel	609	547	439	240	130	10,116,529
9	Lingyuan Iron & Steel	310	344	354	207	164	5,791,360
10	Tonghua Iron & Steel	532	510	513	470	2,147	6,350,058
13	SGIS Songshan	502	504	482	380	1,372	5,290,812
16	Hubei Xinyegang Steel	152	215	204	165	909	6,792,722
18	Xinyu Iron & Steel	931	942	901	849	2,904	9,658,090
21	Jinan Steel	995	947	983	813	781	12,779,942
23	Qingdao Iron & Steel	309	300	287	228	333	5,703,437
24	Anyang Iron & Steel	996	1,009	915	909	1,402	13,026,100
26	Wuhan Iron & Steel	1,601	1,685	1,529	699	5,096	16,783,116
30	Lianyuan Steel	633	644	623	475	1,404	11,211,045

Note. CRS = constant return to scale.

Shuicheng Iron & Steel and Huibei Iron & Steel, exhibit DRS and need to decrease their scale to attain better scale efficiency. Most of the DMUs, however, exhibit IRS. For these steel makers, such as Baotou Iron and Steel and Lingyuan Iron & Steel, their inefficiency is partially or totally caused by their relative small scale.

Furthermore, we also calculate the target values for the inefficient DMUs to use for improvement. Based on the CRS DEA approach, the targets for the inefficient steel makers are shown in Table 6, and these targets should be used for increasing both technical and scale efficiency. Take Baotou Iron & Steel for example; it needs to increase pig iron production, crude iron production, and finished steel production to 995, 1,037, and 978, respectively, and reduce waste water, waste gas, and waste solid to 394, 779, and 10,449,413, respectively, in order to become efficient.

Discussion

Environmental Efficiency Scores

This article constructs nonradial DDF models to measure environmental efficiency and applies them to evaluate the performance of 30 major Chinese iron and steel makers. The models allow evaluation of the environmental efficiency of DMUs considering the performances regarding both desirable and undesirable outputs. Different from the existing nonlinear nonradial DDF models, our new models use linear programming based on the idea of SOCP. Another advantage of our models is that they show the performance regarding desirable and undesirable outputs separately; this level of detail allows inefficient DMUs to obtain target values for both desirable and undesirable outputs to improve their performance to full efficient.

The empirical results indicate the environmental efficiency of the 30 major iron and steel makers considering three desirable outputs (pig steel, crude iron, and finished steel), together with emissions of three undesirable outputs (waste water, waste gas, and waste solids). Nearly half of the evaluated steel makers (13 in 30) are inefficient regarding technical efficiency or scale efficiency. Some of them, such as Baotou and Wuhan Iron & Steel, perform poorly with an environmental efficiency lower than 0.5. All the inefficient steel makers can be divided into three categories based on the results: Some of them need to improve their performance by increasing production of desirable outputs, while the majority needs to improve their performance by decreasing the emission of undesirable outputs by maintaining or increasing the production of desirable outputs.

By calculating the type of returns to scale, we can find that most of the inefficient steel makers exhibit increasing returns to scale. That means the inefficiency of these iron and steel sectors is caused by their small size to some extent. Moreover, the new presented models supply improvement targets for all the inefficient iron and steel makers to reach efficiency based on the performance and the existing production level of every sector.

Policies for Efficiency Improvement

Based on the empirical study, we can find that it is necessary for the government to improve the policies of efficiency. Several policies for improving the environmental efficiency of China's iron and steel industry should be described as following:

Policy 1: The overall efficiency of China's iron and steel industry is relatively low, while some of the major iron and steel sectors emit too much pollution at the present level of production. More attention should be paid to decrease the emission of all kinds of pollution through improving environmental efficiency or decreasing the production scale.

Policy 2: Many iron and steel makers attain relatively low environmental efficiency scores, which means that the iron and steel makers with a heavy negative influence on the environment. The large iron and steel factories should be moved out from major cities in China, as they are no longer welcome in the population centers.

Policy 3: There are significant differences on the performance of environmental efficiency between different iron and steel sectors in China. It is a possible way to improve the performance of the industry by decreasing the pollution emissions of poor performed sectors while maintaining or increasing the present level of products. Exactly values of pollution emission and products should be provided by the managers to guide the operation and allocation of resource.

Policy 4: The managers of steel industry should make different plans for improving the efficiency of poor performance steel makers based on the efficiency results rather than decrease emission of pollution only, because there are obvious differences between the performances of different steel makers and the reasons of inefficient results.

Policy 5: Expanding scale and consolidation may be good selections for resolving the problem for some steel makers as most of the steel maker are increasing return to scale or CRS.

Then, we conclude the major policies of China's iron and steel industry during 2010 to 2018 and list them in Table 7. By comparing with the five policies mentioned earlier, we can find that most of the existing policies are focusing on controlling the emission of iron and steel industry by improving production efficiency or decreasing production scale (Policy 1). Some of them could improve the industry structure by adjusting the location or scale of

Table 7. Major Policies of China's Iron and Steel Industry During 2010 to 2018.

Year	Policy	Department	Main content	Relationship
2011	"Notice on elimination of backward production capacity"	The State Council	Decrease the production of steel and iron	Policy 1
	"The 13th five-year plan for iron and steel industry"	Ministry of Industry and Information Technology	Improve the efficiency and quality of development	Policy 1- 5
2012	"Notice on elimination of backward production capacity in 19 industries (2012)"	Ministry of Industry and Information Technology	Decrease the production of steel and iron	Policy 1
	"National ambient air quality standards"	The State Council	Decrease the waste gas emission	Policy 1
2013	"Evaluation indexes for cleaner production in iron and steel industry"	National Development and Reform Commission	Decrease the pollution emission	Policy 1
	"Technical policy for pollution control in iron and steel industry"	Ministry of Ecology and Environment	Decrease the pollution emission through technology	Policy 1
2014	Revision on "Evaluation indexes for cleaner production in iron and steel industry"	Three departments	Decrease the pollution emission	Policy 1
	"Evaluation methods for prevention and control plan of air pollution"	Six departments	Decrease the production scale and pollution emission	Policy 1
	"Treatment schemes for air pollution in key industries around Beijing, Tianjin and Hebei"	Ministry of Ecology and Environment	Decrease the pollution emission around Beijing, Tianjin and Hebei	Policy 1 and Policy 2
	"Law of the People's Republic of China on the prevention and control of atmospheric pollution (Draft)"	The State Council	Decrease the pollution emission	Policy 1
2015	"Key work of prevention and control of atmospheric pollution around Beijing, Tianjin and Hebei (2015)"	Beijing Environment Protection Bureau	Decrease the pollution emission and move iron and steel industry from Beijing, Tianjin and Hebei	Policy 1 and Policy 2
	"Standard Conditions for Iron and Steel Industry"	Ministry of Industry and Information Technology	Improve the efficiency and quality of development	Policy 1 and Policy 5
	"Transition and upgrading plan for iron and steel industry (2015–2025)"	Ministry of Industry and Information Technology	Improve the efficiency and quality of development	Policy 1-5

(continued)

Table 7. Continued

Year	Policy	Department	Main content	Relationship
2016	"Views on elimination of backward production capacity"	The State Council	Decrease the production of steel and iron	Policy 1
	"Upgrading plan for iron and steel industry (2016-2020)"	Ministry of Industry and Information Technology	Improve the efficiency and quality of development	Policy 1-5
	"Notice about development specialized examination on environment protection in key industries"	Ministry of Ecology and Environment	Decrease the pollution emission	Policy 1
2017	"Notice on promoting supply-side reform in iron and steel industry with the methods of policy and price"	Ministry of Industry and Information Technology and National Development and Reform Commission	Decrease the production of steel and iron	Policy 1
	"Design standards for energy efficiency of iron and steel industry"	State administration for Market regulation	Decrease the resource consumption	Policy 1
2018	"Transformation plan for ultra-low emission in iron and steel industry"	Ministry of Ecology and Environment	Decrease the pollution emission	Policy 1
	"Tax law of the People's Republic of China on environment protection"	The State Council	Decrease the pollution emission	Policy 1
	"Notice on Capacity replacement in iron and steel, cement and glass industries"	Ministry of Industry and Information Technology	Improve the efficiency and quality of development	Policy 1 and Policy 3

iron and steel sectors (Policies 2 and 5). However, there are inadequate policies to guide the resource allocation or reallocation among different iron and steel sectors. Besides, we also find that nearly all the policy focus on guiding the action of whole industry, but few of them could consider individual characteristics.

Implications for Conservation

This article focuses on measuring the environmental efficiency of major iron and steel sectors in China while considering both desirable and undesirable outputs. A set of nonradial DDF have been constructed to calculate the scale desirable output and undesirable output with different efficiency scores. The new proposed models can resolve the problem on efficiency calculation based on the traditional nonradial DDF and provide more accurate efficiency results. Then, these models evaluate the major iron and steel sectors in China. The empirical study shows that many China's iron and steel sectors perform poorly on environmental efficiency and there are spaces for them to improve their performance. In addition, by comparing the efficiency scores obtained by using nonradial models, we can find there are difference between the performance on desirable output and undesirable outputs for the inefficient iron and steel sectors. Targets for efficiency improvement have been provided based on the efficiency of results in this article.

The article also provides five policies for the managers based on the empirical study which suggest the manager of iron and steel industry to focus on decreasing the emission of pollution, move out iron and steel sectors from population centers, allocate or reallocate the resources for attaining better performance, make different plans for every iron and steel sector while considering its individual characteristics and improve the efficiency scores of iron and steel by expanding scale and consolidation. Then, this article lists the major existing policies in iron and steel industry during 2011 to 2018. It is obvious that a lot of common policies for the whole industry have been proposed during the past years, while few of them consider the individual characteristics for each iron and steel. In the future, more flexible and specific policies should be provided for each iron and steel sector based on its performance results. Also, the managers need to make some policies to improve the environmental efficiency of the whole industry through allocation or reallocation on inputs among the iron and steel sectors based on their performance.

Further research might investigate the following points: (a) Due to limited data resources, only data from 2010 are used in the empirical study; data in more recent years should be analyzed in the future. (b) In the presented no-radial DDF models, all the desirable (undesirable) outputs are assumed to be equally important, that is, each output is weighted equally. For example, waste water and waste gas are considered equally harmful to the environment. A refined nonradial DDF method should be investigated to evaluate the performance of DMUs on each desirable (undesirable) output separately.

Appendix

We do the following to transform the nonlinear model (Equation 5) into a linear program. Following the idea of SOCP, we let $1+\beta_0^{*}=\psi_0$, $1-\beta_0^{b*}=\frac{1}{\delta_0}$, and $\theta_0=\frac{1}{\delta_0\psi_0}$ so model (Equation 5) can be reformulated as:

$$\begin{aligned}
&Min:\ \theta_0\\
&\sum_{j=1}^{n}\lambda_j x_{ij}\ \le\ x_{i0},\ i=1,2,\ldots,m.\\
&\sum_{j=1}^{n}\lambda_j y_{rj}\ge\frac{1}{\delta_0\theta_0}y_{r0},\ r=1,2,\ldots,s.\\
&\sum_{j=1}^{n}\lambda_j y_{tj}^{b}\ \le\ \frac{1}{\delta_0}y_{t0}^{b},\ t=1,2,\ldots,w.\\
&1\ge\theta_0\ge0,\delta_0\ge1,\lambda_j\ge0,j=1,2,\ldots,n
\end{aligned}\tag{A1}$$

Model (Equation A1) is equivalent to model (Equation 5). Because $\delta_0\ge1$, we can let $\tau_j=\lambda_j\delta_0$ and rewrite model (Equation A1)as follows:

$$\begin{aligned}
&Min:\ \theta_0\\
&\sum_{j=1}^{n}\tau_j x_{ij}\ \le\ \delta_0 x_{i0},\ i=1,2,\ldots,m.\\
&\sum_{j=1}^{n}\tau_j y_{rj}\ge\frac{1}{\theta_0}y_{r0},\ r=1,2,\ldots,s.\\
&\sum_{j=1}^{n}\tau_j y_{tj}^{b}\ \le\ y_{t0}^{b},\ t=1,2,\ldots,w.\\
&1\ge\theta_0\ge0,\delta_0\ge1,\lambda_j\ge0,j=1,2,\ldots,n
\end{aligned}\tag{A2}$$

In addition to the optimal condition, we can add several slack variables to model (Equation A2) to transform the constraints to equalities.

$$Min\ \ \theta_0\tag{A3}$$

$$\sum_{j=1}^{n}\tau_j y_{rj}\ge\frac{1}{\theta_0}y_{r0},\ r=1,2,\ldots,s.\tag{A4}$$

$$\sum_{j=1}^{n}\tau_j x_{ij}=\delta_0 x_{i0}-d_{ix},\ i=1,2,\ldots,m.\tag{A5}$$

$$\sum_{j=1}^{n}\tau_j y_{tj}^{b}=y_{t0}^{b}-d_{tb},\ t=1,2,\ldots,w.\tag{A5}$$

$$\theta_0+d_0^{\theta}=1,\tag{A6}$$

$$\delta_0-d_0^{\delta}=1,\tag{A7}$$

$$\theta_0,\delta_0\,is\ free\tag{A8}$$

$$d_0^{\theta}\ge0,d_0^{\delta}\ge0,d_{ix}\ge0,d_{tb}\ge0,\tau_j\ge0,j=1,2,\ldots,n\tag{A9}$$

Constraint (Equation A4) can be rewritten as $\left(\frac{\sum_{j=1}^{n}\tau_j y_{rj}+\theta_0}{2}\right)^2\ge\left(\frac{\sum_{j=1}^{n}\tau_j y_{rj}-\theta_0}{2}\right)^2+\left(\sqrt{y_{r0}}\right)^2$. Then, constraints (Equation A1), (Equation A8), and (Equation A9) correspond to a second-order cone and a second-order cone programming method can be defined.

Let $\Re^k$ be the nonnegative Euclidean k-orthant. Then the second-order cone is defined as

$$\Delta_k=\left\{\omega\in\Re^k\,\middle|\,\omega_1\ge\sqrt{\sum_{\ell=2}^{k}\omega_\ell^2}\right\}\tag{A10}$$

Then, the nonradial DDF model is changed into the following linear program:

$$\begin{aligned}
&Min:\ \theta_0\\
&\sum_{j=1}^{n}\tau_j y_{tj}^{b}-y_{t0}^{b}+d_{tb}=0,\ t=1,2,\ldots,w.\\
&\sum_{j=1}^{n}\tau_j x_{ij}-\delta_0 x_{i0}+d_{ix}=0,\ i=1,2,\ldots,m.\\
&\theta_0+d_0^{\theta}=1\\
&\delta_0-d_0^{\delta}=1\\
&\left|\begin{matrix}\frac{\sum_{j=1}^{n}\tau_j y_{rj}-\theta_0}{2}\\ \sqrt{y_{r0}}\end{matrix}\right|_2\le\frac{\sum_{j=1}^{n}\tau_j y_{rj}+\theta_0}{2}\\
&\tau_j,d_{tb},d_{ix},d_0^{\theta},d_0^{\delta}\ge0
\end{aligned}\tag{A11}$$

The model based on the VRS assumption is shown as model (Equation 7) in the main text.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research is financially supported by the National Natural Science Foundation of China (71701059 and 71801068).

ORCID iD

Tao Ding https://orcid.org/0000-0002-2447-3780

References

Brunke, J. C., Johansson, M., & Thollander, P. (2014). Empirical investigation of barriers and drivers to the adoption of energy conservation measures, energy management practices and energy services in the Swedish iron and steel industry. *Journal of Cleaner Production*, *84*, 509–525.

Chambers, R. G., Chung, Y., & Färe, R. (1996). Benefit and distance functions. *Journal of Economic Theory*, *70*(2), 407–419.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal of Operational Research, 2*, 429–444.

Chen, J., Xu, C., Song, M., & Liu, X. (2018). Driving factors of China's energy productivity and its spatial character: Evidence from 248 cities. *Ecological Indicators*, *90*, 18–27.

Chen, W., Yin, X., & Ma, D. (2014). A bottom-up analysis of China's iron and steel industrial energy consumption and CO2 emissions. *Applied Energy*, *136*, 1174–1183.

China Iron and Steel Association. (2011). *China iron and steel statistics annual report*. *Beijing*, China: CISA Statistics and Information Committee [in Chinese].

China Iron and Steel Association. (2011). *China iron and steel industry environmental statistics annual report*. Beijing, China: CISA Environmental Protection and Energy Saving Committee [in Chinese].

Chung, Y. H., Färe, R., & Grosskopf, S. (1997). Productivity and undesirable outputs: A directional distance function approach. *Journal of Environmental Management*, *51*(3), 229–240.

Faere, R. , Grosskopf, S. , Lovell, C. A. K. , & Pasurka, C. (1989). Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *The Review of Economics and Statistics, 71*(1), 90–98.

Hasanbeigi, A., Morrow, W., Sathaye, J., Masanet, E., & Xu, T. (2013). A bottom-up model to estimate the energy efficiency improvement and CO2 emission reduction potentials in the Chinese iron and steel industry. *Energy*, *50*, 315–325.

He, F., Zhang, Q., Lei, J., Fu, W., & Xu, X. (2013). Energy efficiency and productivity change of China's iron and steel industry: Accounting for undesirable outputs. *Energy Policy*, *54*, 204–213.

International Energy Agency. (2011). *World energy outlook 2011*. Paris, France: Organisation for Economic Co-operation and Development.

Lin, B., & Wang, X. (2014). Exploring energy efficiency in China's iron and steel industry: A stochastic frontier approach. *Energy Policy, 72*, 87–96.

Ma, J., Evans, D. G., Fuller, R. J., & Stewart, D. F. (2002). Technical efficiency and productivity change of China's iron and steel industry. *International Journal of Production Economics*, *76*(3), 293–312.

Mitra Debnath, R., & Sebastian, V. J. (2014). Efficiency in the Indian iron and steel industry–an application of data envelopment analysis. *Journal of Advances in Management Research*, *11*(1), 4–19. ISO 690

Morfeldt, J., & Silveira, S. (2014). Capturing energy efficiency in European iron and steel production—Comparing specific energy consumption and Malmquist productivity index. *Energy Efficiency*, *7*(6), 955–972.

Picazo-Tadeo, A. J., Beltrán-Esteve, M., & Gómez-Limón, J. A. (2012). Assessing eco-efficiency with directional distance functions. *European Journal of Operational Research*, *220*(3), 798–809.

Singh, R. K., Murty, H. R., Gupta, S. K., & Dikshit, A. K. (2007). Development of composite sustainability performance index for steel industry. *Ecological Indicators*, *7*(3), 565–588.

Song, M., Chen, Y., & An, Q. (2018). Spatial econometric analysis of factors influencing regional energy efficiency in China. *Environmental Science & Pollution Research*, *25*(11), 1–15.

Song, M., Wang, J., Zhao, J., Baležentis, T., & Shen, Z. (2018). Production and safety efficiency evaluation in Chinese coal mines: Accident deaths as undesirable output. *Annals of Operations Research*, *2*, 1–19.

Sueyoshi, T., & Sekitani, K. (2007). Computational strategy for Russell measure in DEA: Second-order cone programming. *European Journal of Operational Research*, *180*(1), 459–471.

Wang, Q., Chiu, Y. H., & Chiu, C. R. (2017). Non-radial metafrontier approach to identify carbon emission performance and intensity. *Renewable and Sustainable Energy Reviews*, *69*, 664–672.

Wang, Q., Su, B., Zhou, P., & Chiu, C. R. (2016). Measuring total-factor CO2 emission performance and technology gaps using a non-radial directional distance function: A modified approach. *Energy Economics*, *56*, 475–482.

Wei, Y. M., Liao, H., & Fan, Y. (2007). An empirical analysis of energy efficiency in China's iron and steel sector. *Energy*, *32*(12), 2262–2270.

Wu, H. Q., Shi, Y., Xia, Q., & Zhu, W. D. (2014). Effectiveness of the policy of circular economy in China: A DEA-based analysis for the period of 11th five-year-plan. *Resources, Conservation and Recycling*, *83*, 163–175.

Wu, J., & Zhou, Z. (2014). Environmental efficiency of Chinese paper mills along Huai river: A data envelopment analysis (DEA) based study. *Environmental Engineering & Management Journal*, *13*(5), 1101–1109.

Xu, B., & Lin, B. (2016). Assessing CO_2 emissions in China's iron and steel industry: A dynamic vector autoregression model. *Applied Energy*, *161*, 375–386.

Zhang, N., & Choi, Y. (2013). Total-factor carbon emission performance of fossil fuel power plants in China: A metafrontier non-radial Malmquist index analysis. *Energy Economics*, *40*, 549–559.

Zhang, S., Worrell, E., Crijns-Graus, W., Wagner, F., & Cofala, J. (2014). Co-benefits of energy efficiency improvement and air pollution abatement in the Chinese iron and steel industry. *Energy*, *78*, 333–345.

Zhou, P., Ang, B. W., & Wang, H. (2012). Energy and CO2 emission performance in electricity generation: A non-radial directional distance function approach. *European Journal of Operational Research*, *221*(3), 625–635.

Zhou, Z., Guo, X., Wu, H., & Yu, J. (2018). Evaluating air quality in China based on daily data: Application of integer data envelopment analysis. *Journal of Cleaner Production*, *198*(10), 304–311.