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A DR-DEA PRODUCTION SUPPLIER SELECTION MODEL FOR GREEN MANUFACTURING CONSIDERING POLLUTANT DISCHARGE

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Abstract

The coal-fired heating pours a large volume of sulfur dioxide, nitrogen oxides, dust and other pollutants to the atmosphere, resulting in a serious impact to environmental air quality. It is not economic to improve the filtration technology simply, so controlling the source discharge is a method to be explored. As the main source of coal, suppliers' coal quality should be the guarantee of pollutant emission control. Thus, how to select a fewer pollutants of coal suppliers while considering economic benefit has become a critical question. Combining with the characteristics of government procurement, the research converts the supplier selection of coal procurement to the efficiency evaluation of decision-making units. On the bases of traditional Data envelopment analysis(DEA), this research introduces a pollutant-type attribute as undesirable outputs of DEA and then presents a model for supplier evaluation considering pollutant discharge (DR-DEA, Directional Russell-DEA). This model, which combined the advantages of directional distance function and enhanced Russell measure, can be quickly convergent solution space and effectively avoid unfairness caused by decision maker's corruption subjectivity during the supplier selection. It is found that when considering the emission of pollutants, within the range of low calorific value and paying a certain capital cost to choose the environmental protection coal supplier can greatly reduce the emission of pollutants, thus reducing the environmental pollution. Finally, the objectivity and validity of the presented model are verified by analyzing and comparing some examples.

Key words: data envelopment analysis (DEA), government procurement, pollutant discharge, supplier selection

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1. Introduction

In recent years, more than 30 provinces and cities in China, such as Beijing and the Hebei Province, have experienced large-scale, sustained haze weather, which has done serious harm to the living environment and to the health of residents. According to research findings, sulfur dioxide (SO_2), nitrogen oxides (NO_x), and other pollutants discharged by coal-fired heating plants in northern China during winter are the main causes of haze (Yang et al., 2015). As shown by the data in the China Statistical Yearbook, in 2018 the total amount of coal used for heating in China was 300 million tons. It is predicted that in the next 10 years, coal will still serve as the dominant energy source for heating in China (Ding et al., 2019). Coal is the main resource used for heating in most areas of northern China, and produces large quantities of pollutants such as SO_2, NO_x, smoke, and dust, which have a serious impact on environmental quality. At the present stage, it is uneconomical to solely rely on the improvement of coal filtering technology to solve the problem of pollutant emissions, and it is necessary to explore the possibility to control pollutant emissions at source. In addition, the quality of coal, which is mainly provided by coal suppliers, is a guarantee to control pollutant emissions. Therefore, from the perspective of green purchasing, it is worth further investigating the problem of how to select coal suppliers with better

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comprehensive benefits, including the control of pollutant emissions at source, at the same time, economic benefits should be considered

The issue of coal supplier selection can be considered as a multi-attribute decision-making issue. It is usually performed through public bidding by the government, following the principles of openness and justice. In this process, traditional methods to select suppliers focus mainly on economic benefits, such as the method of the Lowest Price (LP) (Jeong and Choi, 2019), which is applicable only to products or services whose price is the only distinguishing standard. With the diversification of products and the development of the government purchasing principle of "good value for money" (Jasiukevicius and Vasiliauskaite, 2018), when purchasing energy sources, apart from elements such as price and product life cycle, the government started to pay more attention to environmental benefits, i.e., the effects of pollutant emissions on the environment. For this reason, the LP method is not applicable to supplier selection in this context. With regard to this limitation, the price and the CO_2 emissions of power generation were comprehensively considered by Fang et al. (2013), and the utility function and the scoring function were used to sort suppliers, achieving better results. However, this method entails subjectivity in the determination of the weight of each attribute, which is contrary to the principles of government purchase. To settle this problem, a nonparametric data envelopment analysis (DEA) model (Thies et al., 2019; Zhang and Cui, 2019) was introduced for supplier selection. The DEA is a model for the evaluation of relative efficiency based on data; by comparing the input and output performance of decision unit (DMU) with that of other DMUs, it is possible to assess its relative efficiency (Laurens et al., 2015). In essence, the DEA model is a tool to determine the efficiency of a DMU based on linear programming. Its advantage is that it is not necessary to consider the functional relationship between input and output, and in most cases, there is no need to set weight assumptions. Therefore, it is possible to effectively avoid subjectivity in selecting and sorting. The DEA model has been widely applied to evaluate the efficiency of banks, education institutions, hospitals, and other subjects (Calamar et al., 2017; Wu et al., 2013). With regard to the issue of supplier selection, in this paper, suppliers are sorted according to cross efficiency, obtaining better results. However, in that model, only desirable outputs have been taken into consideration (Falagario et al., 2014), while undesirable outputs, such as pollutant emissions, failed to be addressed.

Previous research employed the nonparametric directional distance function (DDF) method and, by increasing desirable outputs and decreasing undesirable outputs in the same proportion, established a model for the evaluation of airport operation efficiency based on undesirable outputs (Song et al., 2020). However, the desirable outputs and the undesirable outputs are not the same increase and decrease, the model is therefore inconsistent with reality.

Through a general survey of existing studies, it is possible to acknowledge that in the field of government purchasing, there are a limited number of studies on supplier selection that consider undesirable outputs such as pollutant emissions. The traditional DEA model has some limitations in dealing with undesirable outputs. To address these limitations, in this study coal suppliers were taken as the DMU of the DEA model, in combination with the characteristics of government purchasing, and a DR-DEA model based on DDF and the enhanced Russell measure (ERM) was established to effectively avoid the subjectivity in coal supplier selection, while at the same time considering undesirable outputs as pollutant emissions. Then, the model was solved to obtain the desirable output efficiency, undesirable output efficiency, and overall efficiency of the DMU, which can be used by decision makers as criteria to evaluate and select coal suppliers. Finally, the validity of the model was verified using examples, and a comparison was made with existing research methods. In the remainder of this paper, we first introduce the Supplier selection model in section2. Our main results are given in Section 3. Finally, Section 4 contains a brief summary.

2. Materials and methods

In China, the purchase of coal for heating is usually carried out through public bidding by the government, and it is necessary to evaluate multiple coal suppliers and select the best one. As the DEA model can better evaluate the effectiveness of multiple DMUs, the issue of coal supplier selection can be transformed into an issue of sorting DMUs in the DEA model. In the traditional supplier selection method, the attributes for the evaluation of suppliers are classified into cost-focused and benefit-focused attributes.

From the perspective of decision makers, cost-focused attributes refer to the attribute of "the smaller, the better", such as product price, while benefit-focused attributes refer to the attribute of "the greater, the better", such as product quality. In literature, suppliers are considered as DMUs in the DEA model, and the cost-focused attribute and the benefit-focused attribute for suppliers' evaluation are taken as inputs and outputs of DEA, respectively, without considering undesirable outputs. However, several pollutants are discharged in the process of coal burning, and the government needs to consider the influence of pollutants on the environment, by choosing the type of coal that discharges lower quantities of pollutants. Pollutants are emitted as a by-product of heating proportionally with coal consumption, and should be considered as undesirable outputs.

To distinguish pollutant emissions from cost-focused attributes such as price, in this study the pollutant emissions were classified as pollutant attribute (the cost-focused attributes mentioned below do not include pollutant emissions). Therefore, a key problem to address is how to solve the model for coal supplier selection considering pollutant emissions.

2.1. Formal representation of related parameters

More into detail, the government purchases coal for heating through public bidding; after a preliminary selection, there are n suppliers meeting the requirements, denoted by $a_1,...,a_n$ and the decision makers choose the attribute set to evaluate the suppliers according to the purchase requirement and purpose, denoted by $A=(A^C,A^{be},A^p)=(at_1^C,...at_{mc}^c;at_1^{be},...at_{mbe}^{be};at_1^p,...a_{mp}^p)$,while A^C, A^{be} and A^p denote the cost-focused attribute set, the benefit-focused attribute set, and the pollutant attribute set, respectively. In terms of supplier a_i, its attribute set is $A_i=(A_i^C,A_i^{be},A_i^p)$ and $A_i^C=(at_{1i}^C,...at_{mc}^C i)$ $A_i^{be}=(at_{1i}^{be},...at_{mbe_{be}}^{be} i)$ $A_i^p=(at_{1i}^p,...at_{me}^p i)$.

The basic meanings of the parameters in the DEA model are as follows $DMU_k k=1,2,...,K$ $x=(x_1,x_2,...,x_N)\in R_+^N$ denotes the input vector of the model; $u=(u_1,u_2,...,u_M)\in R_+^M$ denotes the desirable output; $b=(b_1,b_2,...,b_J)\in R_+^J$ denotes the undesirable output; output vector is denoted by. $y=(u,b)=(y_1,y_2,...y_G)\in R_+^G$ $x_k=(x_{1k},x_{2k},...x_{Nk})\in R_+^N$ denotes the input of each DMU; $u_k=(u_{1k},u_{2k},...,u_{Mk})\in R_+^M$ denotes its desirable output; and $b_k=(b_{1k},b_{2k},...b_{jk})\in R_+^J$ denotes its undesirable output(Table 1). The model solving process was based on the attribute set provided by suppliers, where the cost-focused attribute was taken as input, the benefit-focused attribute as desirable output, and the pollutant attribute as undesirable output. The relative efficiency of each supplier was calculated through the improved DEA model.

2.2. Research hypotheses

The basic hypotheses of this study are as follows:

Hypothesis 1: Candidate coal suppliers are homogeneous, and all the information they provide is true.

Hypothesis 2: For convenience of calculation, it is assumed that each supplier provides only one type of coal, and that the coal supply of each supplier can meet the demand of coal in the bidding.

Hypothesis 3: For purchasers, it is the case that “the greater each attribute value, the better” or “the smaller each attribute value, the better”, that is, there is no optimal interval value.

Hypothesis 4: Pollutant attribute satisfies random weak disposability, that is, under the given cost-focused attribute, a feasible way to reduce pollutant emissions is to simultaneously reduce benefit-focused attributes.

Hypothesis 5: Pollutant attributes and benefit-focused attributes satisfy the zero-correlation assumption, that is, producing benefit-focused attributes will inevitably be accompanied by pollutant emissions, unless no coal is burnt.

Hypothesis 6: Benefit-focused attributes and cost-focused attributes satisfy the random disposability assumption, i.e., $\sum_{i\in n}\lambda_i at_{si}^{be}\ge at_{si}^{be}, s=1,...m_{be}, \sum_{i\in n}\lambda_i at_{qi}^{c}\ge at_{qi}^{c}, q=1,...,m_c$ and λ denotes the weight vector.

2.3. The DDF and ERM models

As a nonparametric evaluation method and an effective frontier estimation method, the DEA is generally used to evaluate the relative efficiency of homogeneous DMUs with multiple inputs and outputs. Farrell defined the efficiency of DMUs as the ratio of the actual output level to the frontier output level. Under the condition that the appointed maximum relative efficiency is equal to 1, the above-mentioned method to calculate relative efficiency is not applicable.

The DDF is generally used to solve the efficiency problem involving undesirable outputs; its principle is to measure the efficiency of a DMU by gauging its distance from an effective frontier (Podinovski, 2019). During the calculation of the DDF, decision makers can set the improvement direction according to their will, and improve efficiency by radically increasing desirable outputs, while at the same time decreasing undesirable outputs. The DDF based on the perspective of output was defined as follows (Eq. 1):

$$\vec{D}(x,u,b;g)=\sup\{\beta:(x,u+\beta g_u, b-\beta g_b)\in P(x)\} \quad (1)$$

Table 1. Formal description of parameters in models

	Supplier selection	***DEA Model***
Supplier/DMU	$a_1,...,a_n$	$DMU_k k=1,2,...,K$
cost-focused attribute/ input	$A^c=(at_1^c,...at_{mc}^c)$	$x=(x_1,x_2,...,x_N)\in R_+^N$
benefit-focused attribute/ desirable output	$A^{be}=(at_1^{be},...at_{m_{be}}^{be})$	$u=(u_1,u_2,...,u_M)\in R_+^M$
pollutant attribute/ undesirable output	$A^p=(at_1^p,...at_{m_e}^p)$	$b=(b_1,b_2,...,b_J)\in R_+^J$

where: *vector* $g=(g_u,g_b)$ denotes the direction of improvement set by decision makers; β maximum improvement multiple; $P(x)$ denotes the possible set for outputs (Fig. 1), in the possible set for outputs , $P(x)$ DMUs 1, 2, and 5 are at the production frontier, with a relative efficiency of 1.DMU 4 can have multiple directions, e.g., the two improvement direction vectors $g=(u,0)$ and $g=(0,b)$ marked in the figure. Decision makers can decrease inputs and increase outputs according to their settings.

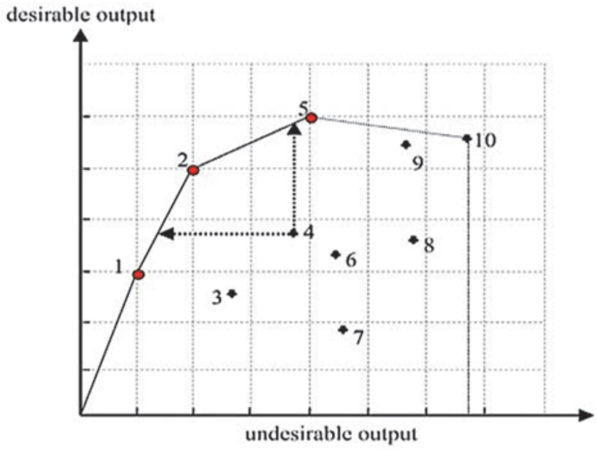

Fig.1. Directional distance function

As shown in (Eq. 1), the radial DDF method needs to improve the consistency between the desirable output and the undesirable output. However, in the case of non-zero slackness condition, the efficiency obtained through this radial method may be overestimated (Li and Lin, 2017). To solve this problem, a DEA model considering ERM was employed.

This model is non-radial and considers both inputs and outputs; its efficiency index is the ratio of the weighted average of input efficiency to that of output efficiency (Wu et al., 2015), as shown byEqs.(2-3):

$$Min\,\theta=\frac{1}{N}\sum_{n=1}^{N}\theta_n \,/\, \frac{1}{G}\sum_{g=1}^{G}\varphi_g, 0\le\theta_n\le 1, \varphi_g\ge 1, z_k\ge 0,\ k=1,...K \tag{2}$$

$$s.t.\sum_{k=1}^{K}z_k x_{nk}\le\theta_n x_{n0}, n=1,...,N;\sum_{k=1}^{K}z_k x_{gk}\ge\theta_n y_{go},\ g=1,...G \tag{3}$$

where: z_k denotes the weight, and θ denotes the efficiency of DMUs. This method overcomes the following three limitations of employing the DDF: it fails to consider inputs and outputs simultaneously; inputs or outputs undergo radial variation; and the efficiency index fails to consider cases where the input or the output is slack.

Therefore, in this paper, by combining the advantages of DDF and ERM, a supplier selection model (DR-DEA model) was established, considering pollutant emissions as undesirable attribute.

2.4. The DR-DEA model based on DDF and ERM

In this paper, a DEA model for undesirable outputs was established (Chen et al., 2015), and that both desirable and undesirable outputs are needed to determine a supplier's relative efficiency, in this model, the vector of improvement direction was set as $g=(u^k,b^k)$, and the model formula employed, based on the perspective of output, is as follows Eqs. (4-6):

$$\vec{D}(x^{k^{'}},u^{k^{'}},b^{k^{'}};g)=\beta^R=\max\frac{1}{2}\left(\frac{1}{M}\sum_{m=1}^{M}\beta_{mk^{'}}^{u}+\frac{1}{J}\sum_{j=1}^{M_e}\beta_{jk^{'}}^{b}\right) \tag{4}$$

$$s.t.\sum_{k=1}^{K}z_k u_{mk}\ge(1+\beta_{mk^{'}}^{u})u_{mk^{'}}, m=1,...,M; z_k\ge 0, k=1,...,K \tag{5}$$

$$\sum_{k=1}^{K}z_k b_{jk}=(1-\beta_{jk^{'}}^{b})b_{jk^{'}}, j=1,...,J;\sum_{k=1}^{K}z_k x_{nk}\ge x_{nk^{'}}, n=1,...,N \tag{6}$$

where: β^R is the ratio of desirable output improvement to undesirable output improvement ; $\beta_{mk'}^{u},\beta_{jk'}^{b}$ - the desirable output ratio increase, and the undesirable output ratio decrease, respectively, for the DMU $k^{'}$ to reach the efficient frontier. As indicated, in this model β^R does not correspond to the relative efficiency of DMU k', but to the relative invalid value of DMU $k^{'}$. This value denotes the total inefficiency of DMU $k^{'}$; correspondingly $\frac{1}{M}\sum_{m=1}^{M}\beta_{mk'}^{u}$ is the inefficiency of the desirable output ; $\frac{1}{J}\sum_{j=1}^{M}\beta_{jk'}^{b}$ is the inefficiency of undesirable output;

β^R is a nonnegative number; and the smaller the value of β^R, the more effective the $DMU\,k^{'}$.

According to the corresponding relationship between each attribute and the input and output of the DEA model in supplier selection, a DR-DEA model considering pollutant emissions was established; its formula is as followsEq.(7-9):

$$\vec{D}(A^{c^{i'}},A^{be^{i'}},A^{e^{i'}};g)=\beta^V=\max\frac{1}{2}\left(\frac{1}{m_{be}}\sum_{s=1}^{m_{be}}\beta_{si^{'}}^{be}+\frac{1}{m_e}\sum_{t=1}^{m_e}\beta_{ti^{'}}^{b}\right) \tag{7}$$

$$s.t.\sum_{i=1}^{n}z_i at_{si}^{be}\ge(1+\beta_{si^{'}}^{be})at_{si^{'}}^{be}, s=1,...,m_{be}; z_i\ge 0, i=1,...,n \tag{8}$$

$$\sum_{i=1}^{n} z_i at_{ti}^{e} = (1-\beta_{ti'}^{e}) at_{ti'}^{e}, t=1,...,m_e; \sum_{t=1}^{n} z_i at_{qi}^{c} \geq at_{qi'}^{c}, \quad q=1,...,m_c \tag{9}$$

where: β^V is the total inefficiency of a supplier; $\beta_{si'}^{be}, \beta_{ti'}^{e}$ - the increased ratio of benefit-focused attributes and the decreased ratio of pollutant attributes; β^V - supplier *i'* is valid; $\beta^V > 0$ - that the supplier is invalid; finally, the smaller the value of β^V, the smaller the inefficiency of a supplier, that is, the higher the relative efficiency of the supplier.

3. Results and discussion

3.1. Determination of attributes for evaluating suppliers

In China, provincial government purchasing centers have been entrusted by provincial governments to conduct open bids for the purchase of coal for the winter period 2014-2015. The purchase conditions were as follows: according to the conditions of heating boilers, the as-received basis net calorific value of coal should be greater than, or equal to, 4,500 kcal/kg, and the quantity of coal to be purchased was set at 123.5 thousand tons. Besides, the public bidding announcement listed the necessary qualifications of qualified bidders, for example, that they guarantee the stability of coal supply, and that they had a business performance of not less than 50,000 tons of coal in at least one of the previous three years.

Input elements. In this paper, the bidding price of each supplier *cp* was taken as the input attribute. Besides, the volatile component *cv* is a main index in coal classification, and has an important reference function in determining the way and technological conditions of coal processing and utilization. The higher the volatile component, the lower the degree of coalification (Guo et al., 2019); therefore, it was also taken as an input attribute.

Desirable output elements. According to the bidding conditions, the low calorific value*ch* was taken as a desirable output.

Undesirable output elements. The main pollutants produced during coal combustion are flue gas and smoke dust. The main pollutants in flue gas are SO_2 and NO_x, which are produced because coal contains sulfur and nitrogen; smoke dust is mainly composed of incombustible mineral particles, and it is produced due to the presence of incombustible ash in coal.

Because the emission of pollutants is affected by several factors such as coal quality, boiler condition, and combustion condition, it is difficult to directly obtain accurate emission data. According to the law of conservation of mass, in this experiment, the emission loads of SO_2, NO_x, and smoke dust were calculated through the sulfur, nitrogen, and ash content in coal and the corresponding calculation formula, and were taken as three undesirable outputs. Under normal circumstances, the content of combustible sulfur accounts for 70%-90% of total coal sulfur content; accordingly, in this paper the average value of 80% was taken. Besides, it was assumed that the SO_2 removal rate of the boiler is δ_s and, according to the chemical reaction equation $S+O_2=SO_2$, the formula employed to calculate the SO_2 produced per kilogram of coal is as follows (Eq. 10):

$$G_{SO2} = 2*80\%*Sad*(1-\delta_s) \tag{10}$$

Similarly, the formula used to calculate NO_2 produced per kilogram of coal is as follows (Eq. 11):

$$G_{NO2} = 1.63*(\sigma * Nad + 0.000938) \tag{11}$$

The formula used to calculate the smoke dust produced per kilogram of coal is as follows (Eq. 12):

$$G_{dust} = Aad * df * (1-\delta_{dust}) \tag{12}$$

where: $G_{SO2}, G_{NO2}. G_{dust}$ - the emission loads of SO_2, NO_x and smoke dust, respectively; σ -the conversion rate of coal to fuel-type *NO*, and in this experiment, it was set as 70%; *Nad*- the nitrogen content in coal; *Aad*-the ash content in coal; *df*-the percentage of smoke dust in the ash of flue gas, which was set at 40%; ∂_{dust} - the overall efficiency of the dust collector, which was set to be 80%.

Therefore, in the bidding announcement, suppliers were required to provide a coal quality inspection report issued by inspection departments, with coal testing qualifications at least equal to, or above the municipal level. If the coal quality inspection report did not contain relevant attribute information, suppliers were required to additionally provide them. Table 2 shows the attribute set for evaluating suppliers in the public bidding.

Table 2. The attributes of supplier evaluation in coal-fired heating procurement

Symbol	*Product attributes*	*Transform attributes(unit)*	*Type*
cp	coal price	coal price(RMB/kg)	Input
cv	volatile component	volatile component (Vad, %)	Input
ch	low calorific value	low calorific value (KCal/kg)	Desirable output
cs	total sulphur	SO_2 emissions per kilogram of coal(kg)	Undesirable output
cn	Nitrogen content	NO_2 emissions per kilogram of coal(kg)	Undesirable output
cd	ash content	dust emissions per kilogram of coal(kg)	Undesirable output

It is assumed that 22 coal suppliers were approved; the relevant attribute values are shown in Table 3.

3.2. Verification of the supplier selection method

According to the DR-DEA model and the attribute information of each supplier, presented in Section 4.1, Matlab R2013b was used to solve. The calculation results are shown in Table 3 and Fig. 2.

1) As can be seen from the last column of Table 3, among 22 suppliers, the suppliers that reached the DEA efficiency include α_3, α_4, α_7, α_{11}, α_{22}, while the other 17 suppliers failed to reach DEA efficiency. This indicates that the model proposed in this paper can effectively reduce the solution space for supplier selection.

2) Fig. 2 shows the impact of environmental ineffectiveness and economic ineffectiveness on overall ineffectiveness. A total of 11 suppliers include α_1, α_2, α_8, α_9, α_{10}, α_{12}, α_{13}, α_{15}, α_{17}, α_{18}, α_{20}, were ineffective due to their low environmental efficiency. When considering the attribute of pollutant emission, the suppliers with high prices and low SO_2, NO_2, and smoke dust emissions, such as α_7, α_{11}, α_4, α_3, had a lower overall ineffectiveness; however, suppliers such as α_{12}, α_{19} had a lower price and higher pollutant emissions, so their relative efficiency was lower. Fig. 2 shows the contribution of economic efficiency and environmental efficiency to the ranking of the suppliers.

3.3. Comparison with existing methods

Comparison with CCR-DEA model without considering pollutant emission. In order to illustrate the impact of pollutant emission on supplier selection, the CCR-DEA model, which does not consider the unexpected output, but only considers the price and low calorific value, is compared with the DR-DEA model proposed in this paper.

Table 3. The values of suppliers' attributes and total inefficiency score

Suppliers	***cp***	***cv***	***ch***	***cs***	***cn***	***cd***	β^V
α_1	0.7800	7.0600	6300	0.8832	0.9828	0.6064	0.1707
α_2	0.7600	5.3400	6450	0.4320	0.7660	0.8336	0.0616
$\boldsymbol{\alpha_3}$	**0.7400**	**6.8800**	**6600**	**0.3744**	**0.5150**	**0.8040**	**0**
$\boldsymbol{\alpha_4}$	**0.8200**	**4.7000**	**6800**	**0.4224**	**0.9143**	**0.6312**	**0**
α_5	0.7500	5.9500	6320	0.9600	1.0627	1.0784	0.2511
α_6	0.7600	7.5300	6170	0.7584	0.6405	1.1512	0.2076
$\boldsymbol{\alpha_7}$	**0.9800**	**3.2800**	**6530**	**0.2592**	**0.7888**	**0.4232**	**0**
α_8	0.7300	8.6100	6150	0.9216	0.7660	0.6696	0.1655
α_9	0.9100	5.7600	6700	0.3936	0.8345	0.5440	0.0368
α_{10}	0.8700	5.7600	6750	0.3936	0.7432	1.0640	0.1105
$\boldsymbol{\alpha_{11}}$	**0.8600**	**5.08**	**6760**	**0.5664**	**0.4009**	**0.6040**	**0**
α_{12}	0.6200	13.6000	6200	2.7840	2.2607	3.6960	0.2128
α_{13}	0.6400	41.3100	4750	0.7200	1.5419	0.5313	0.2647
α_{14}	0.6300	43.4300	4600	0.5760	1.0741	1.1192	0.3486
α_{15}	0.6100	25.3200	4900	0.4320	0.8459	0.5112	0.1495
α_{16}	0.5900	46.7000	4500	0.4320	0.9828	1.1272	0.3051
α_{17}	0.7200	14.5200	6050	0.3936	1.1197	0.6184	0.0813
α_{18}	0.6600	22.8200	5450	0.3936	0.9029	0.5360	0.0811
α_{19}	0.5800	39.8700	4900	1.1616	2.1238	0.6544	0.2936
α_{20}	0.6200	21.5000	5700	2.7456	1.4050	0.8880	0.2149
α_{21}	0.6400	24.0000	5320	1.7088	1.1083	0.9632	0.3176
$\boldsymbol{\alpha_{22}}$	**0.5900**	**12.2400**	**5900**	**1.7568**	**1.5305**	**1.2272**	**0**

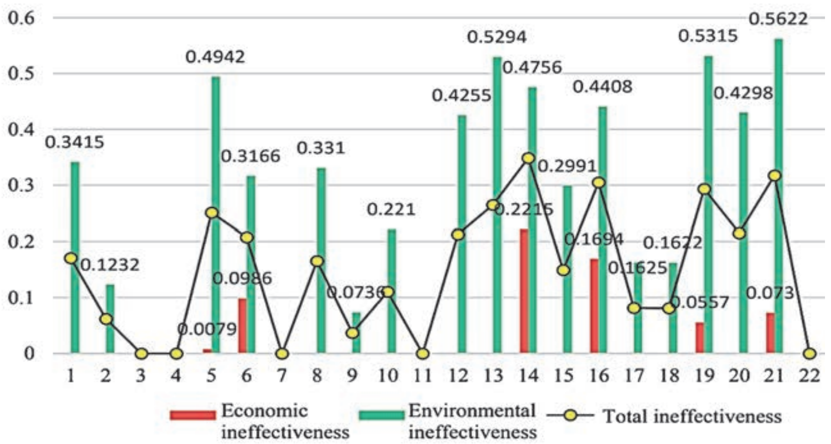

Fig. 2. The influence of environmental inefficiency on total inefficiency

The comparison results are shown in Fig. 3. Since DR-DEA solves the relative inefficiency of suppliers, the CCR-DEA model is used to calculate the efficiency value. It can be seen from Fig. 3 that there are two suppliers in the CCR-DEA model without considering pollutant emission, which are supplier α_{12} and supplier α_{22} respectively. This is because suppliers α_{12} and α_{22} have lower prices and relatively higher calorific value when pollutant emissions are not considered.

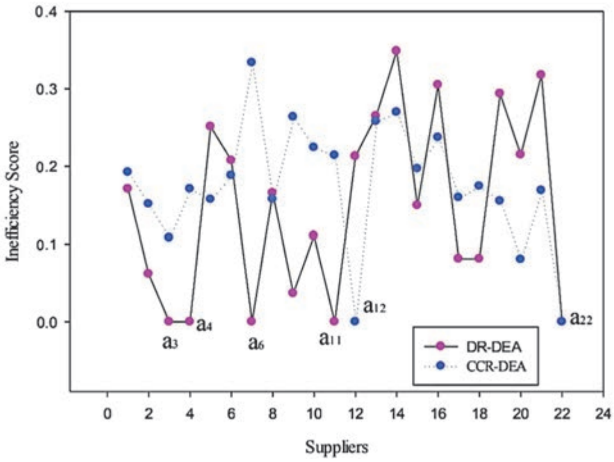

Fig. 3. The comparison of these two models

When using DR-DRA model, the effective supplier is α_3, α_4, α_7, α_{11} and α_{22}, compared with the most expensive effective supplier α_7 and CCR-DEA effective supplier α_{12}, it is found that the price of supplier α_7 is increased by 58%, but the pollutant emission is reduced by 80%. By comparing the lowest effective supplier α_3 with the effective supplier α_{12} of CCR-DEA, it is found that the price of supplier α_3 is increased by 19.6%, but the pollutant emission is reduced by more than 50%.

It can be seen that if the buyer's budget and low calorific value are acceptable, the environmental protection coal supplier can be selected at a certain capital cost, which can greatly reduce the emission of pollutants, thus reducing environmental pollution.

4. Conclusions

In this paper, the nonparametric DEA method was applied to the selection of suppliers for the purchase of coal for heating, and the issue of evaluating suppliers was transformed into the issue of evaluating the relative efficiency of DMUs with multiple inputs and outputs. Besides, pollutant emissions were taken as an attribute in supplier selection, which, together with elements such as price and low calorific value, was used to jointly evaluate suppliers.

Based on the DDF and ERM models, a DR-DEA model considering pollutant emissions was established, which was applied to the selection of suppliers for the purchase of coal for heating. This model does not need to consider the setting of weight and function, and can effectively avoid the unfairness caused by the decision makers' corrupt behaviour. At the same time, this method can help select the suppliers with relatively superior attribute sets, thereby greatly reducing the range of options available, and effectively assisting decision makers in making decisions.

Finally, in this paper, a cause study was conducted to verify the effectiveness and practicability of the method. Two problems need to be further explored in future research: One is that this model was used to calculate the relative efficiency, on the basis that the attribute information provided by all suppliers is true. However, the problem is still open of how to set up corresponding incentive compatibility mechanisms to ensure the authenticity of the information provided by suppliers.

The other one is that in order to be selected by decision makers, there will be competition among suppliers, and game relations between suppliers and governments, both of which have exposed great future research importance.

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