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Research Paper

Energy and environmental efficiency evaluation based on a novel data envelopment analysis: An application in petrochemical industries

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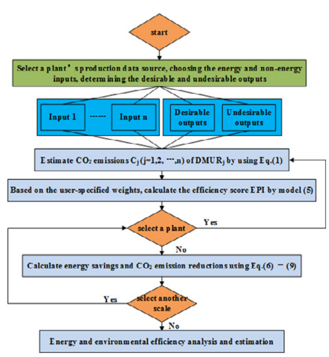
HIGHLIGHTS

- A novel DEA model to estimate the energy and environmental efficiency is proposed.
- The algorithm is applied to the energy and environmental efficiency evaluation of the petrochemical industry.
- Two cases are studied based on the energy and the non-energy inputs, and the desirable and the undesirable outputs.
- Some implications for improving energy efficiency and carbon dioxide emissions reduction in ethylene industries are revealed.

GRAPHICAL ABSTRACT

Above all we have studied, the two ethylene plants have great potential for energy savings and emissions abatement. And we can also provide the production guidance for the energy and environmental efficiency improvement based on the efficiency results obtained from the proposed model, which contribute to environmental protection.



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ABSTRACT

Petrochemical industry is a high energy consumption and heavy pollution industry. Therefore, energy and environmental efficiency evaluation becomes extremely important to achieve sustainable development of the petrochemical industry. This paper proposes a novel DEA model to estimate the energy and environmental efficiency of the petrochemical industry thoroughly. The proposed method introduces the efficiency variable to each energy input and undesirable output and uses environmental performance index (EPI) to represent the overall performance of different decision making units (DMUs). Moreover, the scores of efficiency variables reflect the environmental performance of energy inputs and undesirable outputs, and the larger score represents the greater performance of the DMUs. Meanwhile, the EPI synthesizes the environmental efficiency value of energy inputs and undesirable outputs to help us grasp the energy and environmental comprehensive performance of DMUs, which also contributes to measure the potential of energy saving and emission reduction of petrochemical industry simultaneously. Finally, the proposed model is applied to the energy and environmental efficiency analysis of different ethylene plants under different scales. The experimental results demonstrate the validity of the proposed model and reveal some implications for improving energy efficiency and carbon dioxide emissions reduction of ethylene plants in the petrochemical industry.

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1. Introduction

Since the 1980s, the world economy and industrial production has undergone tremendous changes. However, we paid a high environmental price. With the progress of industries, large amounts of greenhouse gas have become a major factor in the environmental deterioration, e.g. global warming, which has drawn many attention of scholars. The petrochemical industry is a typical process industry, and the total energy consumption accounts for about 20% of total industrial energy consumption in China [1]. Ethylene is a typical representative of petrochemical industry. In 2012, for example, the petrochemical companies in China produced 9475 kt/a ethylene and the ethylene output of oil companies was 5110 kt/a, which consumed 579.59 kg and 628.6 kg standard oil per ton, respectively [2,3].

In order to study environmental factors, researchers have explored a variety of approaches based on environmental efficiency technology in recent years. Data Envelopment Analysis (DEA), which was proposed as an evaluation method by the Charnes and Cooper in 1978 to evaluate the effectiveness of the decision-making unit [4], has been widely used in various fields. Based on environmental DEA technology, many researchers evaluated the environmental efficiency from a macro perspective. Bian et al. proposed a non-radial DEA model to evaluate regional energy efficiencies in China [5]. Chen et al. employed data envelopment analysis technique to evaluate environmental efficiency in 30 provinces of China during the period 2001–2010, and conducted hypothesis tests on these environmental efficiencies [6]. In addition, the environmental DEA was also applied in some special areas. Chang et al. analyzed the environmental efficiency of China's transportation sector by proposing a non-radial DEA model with the slacks-based measure (SBM) [7]. Energy and environmental efficiency of agricultural major areas of EU member states were evaluated by Vlontzos et al. based on DEA [8]. However, the application of environmental DEA technology in the petrochemical field was rarely studied.

With regard to the energy efficiency evaluation of petrochemical industry, there is some research on the efficiency evaluation, which can be mainly classified into four categories. The first one is focus on process-oriented optimization. Taylan et al. employed an integrated fuzzy analytical hierarchy process (FAHP) and fuzzy technique for order performance by similarity to ideal solution (TOPSIS) methodologies for the compressor selection [9]. To assess the factors affecting the resilient level of a petrochemical plant, Azadeh proposed a fuzzy cognitive maps (FCMs) method that considers interactions between factors due to their final calculated weights [10]. In addition, some researchers provide an insight into sustainable production in petrochemical industry [11–14], which contributes to investigating and identifying sustainability indicators. The second category interests in the safety culture of the petrochemical production. The expected characters of a safe layout were analyzed and the researches accustomed to propose key indicators of safety management and product system [15–17]. The third category concept brings in the concept of energy efficiency evaluation. Zhu et al. reduced the dimension of data in petrochemical production by combining DEA-CCR model and Principal Component Analysis (PCA) [18]. Geng et al. proposed a DEA Cross Model-based on fuzzy data sets (FDEACM), which obtained direction and the reason of performance improvements for ethylene production process with the help of the Malmquist index which improves DEA Cross Model [19,20]. However, these studies did not consider the environmental efficiency of petrochemical industry, only evaluating the energy efficiency [21–23]. To achieve the sustainable development of petrochemical industry, not only to consider energy conservation but emission reduction also be considered. Thus, the last category is eco-efficiency evaluation in petrochemical production. Abbaszadeh compared eighteen existing methods for assessing eco-efficiency of a petrochemical process [24]. Azadeh et al. assessed the environmental performance and eco-efficiency in a large petrochemical plant using a neuro-fuzzy algorithm, which is the first intelligence algorithm for evaluation of environmental performance [25,26]. To estimate the eco-efficiency of the industrial sector, Charmondusit provided a basic framework for the environmental efficiency evaluation of a petrochemical plant in Thailand [27]. Mannino et al. studied the major Italian chemical industrial area to achieve the factors that influence the evolution of the industrial area [28]. Lang et al. used regression discontinuity to estimate energy savings and environmental performance, and the results confirm the engineering estimates [29]. While in these environmental evaluation, they did not take the energy saving into consideration simultaneously. Moreover, in the efficiency evaluation process of the petrochemical industries did not carry out quantitative analysis.

With respect to the disadvantages above, we proposed a novel DEA model to study the environmental efficiency of the petrochemical industry, which considering energy saving and emission reduction simultaneously. We take ethylene industry production for instance to demonstrate the effectiveness of the proposed model. The results show that it could be used to evaluate and analyze the energy and environmental efficiency of petrochemical industry, and quantifiably offer valuable guidance for energy saving and emission reduction. The proposed method is applicable for the petrochemical industry.

The rest of the paper is organized as follows. Section 2 presents a model to evaluate the energy and environmental efficiency of the ethylene plants, and also we introduce a method based on the proposed model to measure the potential of energy saving and CO_2 emissions reduction. In Section 3, we take the two ethylene plants under different production scales for example to demonstrate the validity of the proposed methodology. Conclusions are described in Section 4.

2. Methodology

Firstly, we introduce the approach for estimating CO_2 emissions. Secondly, we will provide the original DEA model. Based on this origin, the novel DEA model is presented for environmental efficiency evaluation. The last but not the least, this section provides a method for estimating the potential of energy saving and CO_2 reduction.

We consider the real ethylene production per month as a decision-making unit (DMU), there are n independent units, denoted by DMU_j ($j = 1, 2, \ldots, n$). The energy efficiency evaluation of petrochemical industry typically considers five input factors in the literature [9–11], that are crude material of ethylene TTL Feed (o), TTL Fuel (f), TTL Electricity (e), TTL Water (w), TTL Steam (s). The 'TTL' is an abbreviation for 'total'. The small letters in parentheses are the abbreviation of the corresponding inputs. Here, we divide these five kinds of input into two types: energy inputs and non-energy inputs. To explore the environmental efficiency of petrochemical industry, we use TTL Feed, TTL Fuel and TTL Electricity (namely Eo, Ef and Ee, respectively) as three energy inputs, which are relation with carbon dioxide emissions. TTL Water and TTL Steam as two non-energy inputs (namely Ew and Es, respectively), the ethylene production (E) as a desirable output, and CO_2 emissions (C) as an undesirable output.

2.1. Estimation of CO_2 emissions

CO_2 is mainly generated by the energy inputs feed, fuel and electricity in petrochemical process [30]. Thus, we can estimate the CO_2 through multiplying the consumption of every energy input by its carbon dioxide emission coefficient [5]. The approach as Eq. (1):

$$C_j = \sum_{i=1}^{3}(E_{ij} \times F_i) \tag{1}$$

Wherein C_j represents CO_2 emissions of DMU_j (j = 1, 2, . . . , n), i is the index of the three energy inputs (i = feed, fuel and electricity), E_{ij} is the consumption of the energy inputs, the unit of feed, fuel and electricity is GJ/t [19]. F_i represents the carbon dioxide emission coefficient of the energy input i. From the research results we conclude that the F_i is 3.07, 3.24 and 3.56 for feed, fuel and electricity, respectively [30].

2.2. The original model

Data envelopment analysis (DEA) has been extensively studied, and various DEA models were developed, which can be divided into two categories. The first one refers to radial models and oppositely the second could be defined as non-radial models. The 'CCR' is a radial model, which was proposed by Charnes, Cooper, and Rhodes (CCR). CCR is the most representative model while estimating energy efficiency of petrochemical process [18–20]. We choose the CCR as original model to estimate the environmental efficiency of petrochemical industry. The homogeneous decision making units (DMUs) in DEA method are seen as independent each other [31]. To decide the DEA relative efficiency of the DMUs, the weights of inputs and outputs are set as variables, which convey input-output relative efficiency.

Assuming that there are n decision units DMU_j (j = 1, 2, . . . , n), m inputs X and s outputs Y in evaluation system, the j-th input and output index vectors of DMU respectively are $X_j = (x_{1j}, x_{2j}, \ldots, x_{mj})^T > 0$ and $Y_j = (y_{1j}, y_{2j}, \ldots, y_{mj})^T > 0$, j = 1, 2, . . . , n. The weight vectors are $v = (v_1, v_2, \ldots, v_m)^T$ and $u = (u_1, u_2, \ldots, u_s)^T$.

The efficiency evaluation index of DMU_j (j = 1, . . . , n) can be defined as Eq. (2):

$$h_j = \frac{u^T y_j}{v^T x_j}, \; j = 1, \ldots, n. \tag{2}$$

Then the relative efficiency of DMU can be estimate by the output-oriented CCR model (3):

$$\begin{aligned} &\max \;\; \mu^T y_0 \\ &s.t. \begin{cases} \omega^T x_j - \mu^T y_j \geqslant 0, \; j = 1, \ldots, n \\ \omega^T x_0 = 1 \\ \omega, \mu \geqslant 0 \end{cases} \end{aligned} \tag{3}$$

By the theoretical derivation of model 3, we can get the efficiency score of DMUs. The following model 4 is dual model of model 3, which has the same objective value on optimality. The model 4 is usually used to calculate to get efficiency score.

$$\begin{aligned} &\min \;\; \theta \\ &s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j X_j + s_j^+ = \theta X_{j0} \\ \sum_{j=1}^{n} \lambda_j Y_j - s_j^- = Y_{j0} \\ \lambda_j, s_j^+, s_j^- \geqslant 0, \; j = 1, 2, \ldots, n \end{cases} \end{aligned} \tag{4}$$

Wherein X_{j0} represents input vector of the j-th decision unit (DMU_j) and Y_{j0} means the j-th output vector. λ_j represents the weight coefficient of input and output indexes. θ represents reduction ratio of investment, s_j^+ and s_j^- are slack variables. λ_j, θ, s_j^+ and s_j^- are the optimal solutions of the model, which θ reflects the relative efficiency of the decision-making units. If the optimal target value θ^* of linear programming is 1, and the optimal solution $\lambda_j^* > 0$, $s_j^{+*} > 0$, $s_j^{-*} > 0$, we call DMU_j as DEA effective [4].

By directly setting a weighted ratio between input and output, DEA method makes the optimization problem more objective and avoids some subjective factors. It can be seen from the above models, the basic models set an efficiency variable for input uniformly. To further estimate the energy efficiency and environmental performance of petrochemical industry, we propose the novel model.

2.3. The proposed model

The petrochemical production is a joint-production process, i.e. when ethylene is produced by consuming water, steam and energy inputs CO_2 emissions are generated. Thus, it is impossible to increase production and reduce carbon dioxide emissions simultaneously. In this case, the CO_2 emissions should be modeled based on the concept of weak disposability of undesirable output [32,33]. Based on this conception, Färe and Grosskopf provided the environmental DEA technology [33].

As we all know, the consumption of non-energy inputs, i.e. water and steam, does not generated CO_2 emissions. Therefore, we expect to reduce the consumption of energy inputs as much as possible and not cutting back the non-energy in real production. From the perspective of previous study, the non-energy can be treated as fixed inputs, which means that the fixed inputs can be consumed the greater quantity compared to the condition of energy inputs consumption in petrochemical production [5,34]. According to the above points, and following the concept of environmental DEA, we extend the original DEA model CCR to investigate the effects of energy inputs and CO_2 emissions as shown in model (5).

This model shows stronger discriminating power in energy efficiency of petrochemical industry, and considers the efficiency factors of each input. And as we can see in this model, the inputs are divided into two types: energy inputs and non-energy inputs. To estimate the performance of energy inputs, we add environmental variable separately for each energy inputs. Particularly, it also introduces both desirable and undesirable outputs, which is not involved in previous energy efficiency evaluation of petrochemical process [19,20].

$$\begin{aligned} &EPI = \min \tfrac{1}{2}(\omega_o \alpha_o + \omega_f \alpha_f + \omega_e \alpha_e + \theta) \\ &s.t. \begin{cases} \sum_{j=1}^{n} \lambda_j Eo_j + s_o^- = \alpha_o Eo_{jo}, \\ \sum_{j=1}^{n} \lambda_j Ef_j + s_f^- = \alpha_f Ef_{jo}, \\ \sum_{j=1}^{n} \lambda_j Ee_j + s_e^- = \alpha_o Ee_{jo}, \\ \sum_{j=1}^{n} \lambda_j Ew_j + s_w^- = Ew_{jo}, \\ \sum_{j=1}^{n} \lambda_j Es_j + s_s^- = Es_{jo} \\ \sum_{j=1}^{n} \lambda_j E_j - s_E^+ = E_{jo}, \\ \sum_{j=1}^{n} \lambda_j C_j = \theta C_{jo}, \\ \lambda_j, s_o^-, s_f^-, s_e^-, s_w^-, s_s^-, s_E^+, \alpha_o, \alpha_f, \alpha_o, \theta \geqslant 0. \end{cases} \end{aligned} \tag{5}$$

In model 5, environmental performance index (EPI) is the objective function which represents the environmental performance of DMUs. The index of EPI lies in the interval (0, 1], the larger index of EPI, the better performance in energy saving and CO_2 emission reduction. Note that ω_o, ω_f and ω_e are normalized user-specified weights for feed, fuel and electricity, respectively, and $\omega_o + \omega_f + \omega_e = 1$ [5]. The variable α_o, α_f, α_e, θ, λ, s_o^-, s_f^-, s_e^-, s_w^-, s_s^- and s_E^+ be the optimal solution to model 3. The DMU is called DEA efficient if EPI = 1 (i.e. $\alpha_o = 1$, $\alpha_f = 1$, $\alpha_e = 1$ and $\theta = 1$) and all slacks are equal to 0. On the contrary, if EPI < 1, and at this time, there is at least one of α_o, α_f, α_e and θ less than 1, and some slacks are not zero, then we say this DMU is DEA inefficient. Through adjusting slack variable, the inefficient DMU can be efficient.

Based on this novel DEA technology, we can explore the potential energy-saving and CO_2 emission reduction for inefficient DMUs. The calculating approach can be defined as:

$$Os = (1 - \alpha_o)Eo_0 + s_o^- \tag{6}$$

$$Fs = (1 - \alpha_f)Ef_0 + s_f^- \tag{7}$$

$$Es = (1 - \alpha_e)Ee_0 + s_s^- \tag{8}$$

$$Cr = (1 - \theta)C_0 \tag{9}$$

In Eqs. (6), (7), (8), (9), Os, Fs, Es and Cr mean energy saving potential of feed, fuel, electricity and CO_2 reduction target, respectively. We can get valuable information for environmental efficiency enhancement through these equals. The energy and environmental efficiency analysis and estimation of petrochemical industries based on the novel method is described as following:

Step 1: Select the input and output data of a petrochemical plant, and choose the energy and non-energy inputs, determine the desirable and undesirable outputs.
Step 2: Estimate CO_2 emissions C_j (j = 1, 2, ..., n) of DMU_j by using Eq. (1).
Step 3: Based on the given weights ω_o, ω_f and ω_e, calculate the each DMU of the plant's energy and environmental variables' score α_o, α_f, α_e and θ by model (5), and then achieve the environmental efficiency EPI of DMUs.
Step 4: Calculate the goal of energy savings and CO_2 emission reductions of the DMUs of the petrochemical plant through using Eqs. (6)–(9).

Diagrammatically, the implementation procedures of the whole process as shown in flow chart Fig. 1.

3. Application

In this section, we firstly introduce the data source of this study. The data includes the consumption of energy inputs and non-energy inputs, and also the ethylene production. Based on the carbon emission coefficient we calculate the CO_2 emission of ethylene plant every month. Secondly, we compared the efficiency results obtained from the proposed model 5; and then the potential of energy saving and CO_2 emission reduction are measured applying Eqs. (6), (7), (8) and (9), respectively.

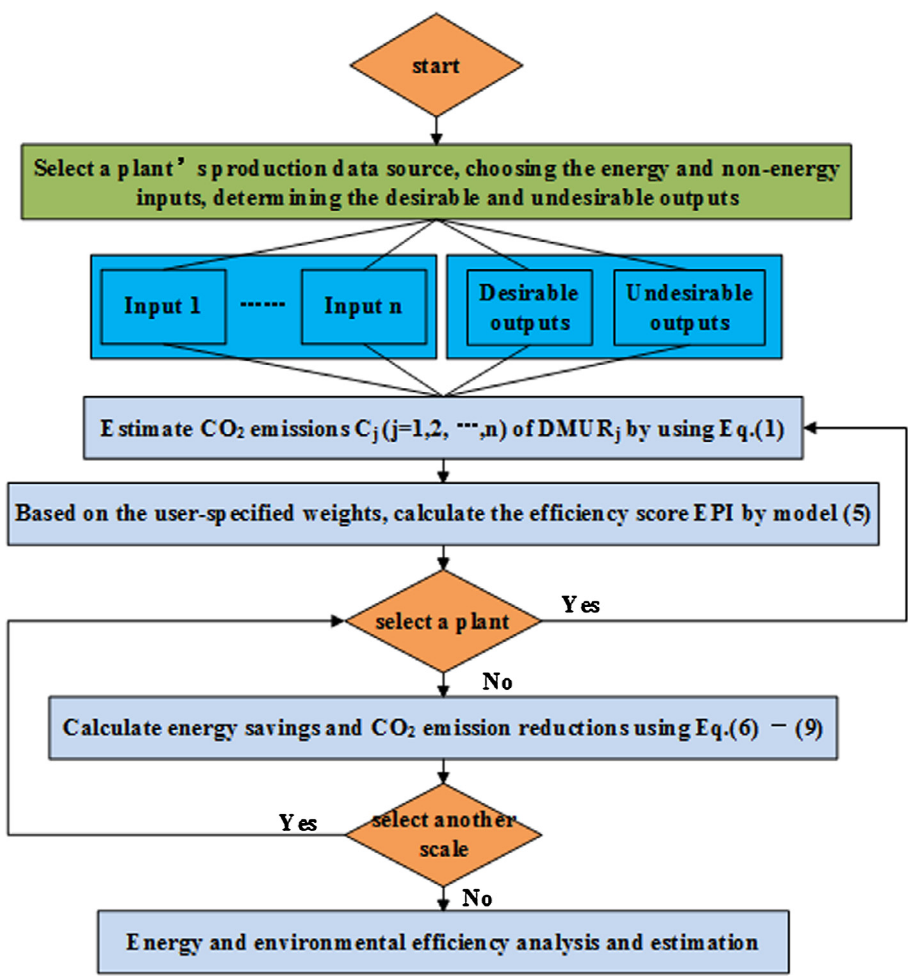

Fig. 1. The flowchart of energy and environmental efficiency evaluation for petrochemical industries.

3.1. Date source

We take ethylene production for example to explore the environmental performance of petrochemical industry. The data sets are of real production per month of two ethylene plants during 2011–2013, we mark as plant 1 and plant 2. We select the two ethylene plants under different product scale to gain more comprehensive results. The ethylene production is considered as one desirable output, CO_2 as one undesirable output, water and steam as two non-energy inputs, feed, fuel and electricity as three energy inputs. According the characteristics of environmental efficiency of ethylene plants production, the general study usually converts measure units of fuel, electricity, water and steam into uniform GJ [35]. This conversion is based on Tables 3.0.2 and 3.0.3 from Energy Consumption Calculation Method of Petroleum Chemical Design (SH/T3110-2001) [36]. The crude material (feed), ethylene yield and CO_2 emission are described in units of 10-thousand tons.

Ethylene production can be divided into two parts as cracking and separation. Cracking section is the main core of the whole ethylene plants. It is also the key equipment of production plants. The majority energy consumption of the ethylene plants comes from the cracking section [35]. It requires a lot of fuel to provide heat for promoting the cracking reaction while the cracking plants are operating. At the same time, quench boiler is producing a large amount of steam by recovering waste heat. To make hydrocarbon reach the best effect in a short time as well as reduce coking, we should inject steam when hydrocarbon is supplied to the cracking equipment. Cracking technology structure consists of two radiant sections and a common convection section, as shown in Fig. 2.

We can conclude from the figure that the energy types include: TTL Water (recycled water, industrial water, boiler water); TTL Steam (ultra-high pressure steam, high pressure steam, low pressure steam); TTL Fuel (fuel gas, light oil, heavy oil); electricity; N2 and compressed gases. Due to N_2 and compressed gas consumption are very low, so we did not take them into consideration while ethylene energy efficiency analysis process [35]. According to statistics, the energy consumption takes up over 50% of the entire ethylene production costs. So the energy consumption of ethylene production include the total investment of fuel(TTL Fuel), the total investment of steam(TTL Steam), the total investment of water (TTL Water) and power (Electricity). Energy consumption makes up the input of ethylene production energy efficiency evaluation, while the output is ethylene production [35].

In order to analyze the energy efficiency of ethylene plants better, we refer to ethylene industry standard DB 37/751–2007 and GB/T 2589–2008 for unified computing [37,38].

The ethylene production data of the two plants are presented as Tables 1 and 2, and the statistics are expressed as average level. CO_2 emission is calculated by using Eq. (1), and Figs. 3 and 4 present the emissions curve of every production month during 2011–2013.

As we can see in Fig. 3, the CO_2 emissions of Aug-11 and Sep-11 of plant 1 plunge to a lower level compared to the average emissions. What makes this situation is that the input of crude material reduced drastically, which are 98,668 t and 115234.76 t respectively, while the average value of feed is 195740.2458 t in 2011.

3.2. Efficiency results

The estimation of environmental efficiency considers the performance of various energy inputs of ethylene production. In model 5, to measure efficiencies of energy consumption with CO_2 emissions disproportionately, we introduced normalized user-specified weights ω_o, ω_f and ω_e. It is based on the specific carbon emissions coefficient to set the preferred weights ω_o, ω_f and ω_e. For simplicity, we can obtain the value by the following calculation:

$$\omega_o = 3.07/(3.07 + 3.24 + 3.56) = 0.311,$$
$$\omega_f = 3.24/(3.07 + 3.24 + 3.56) = 0.328,$$
$$\omega_e = 3.56/(3.07 + 3.24 + 3.56) = 0.361.$$

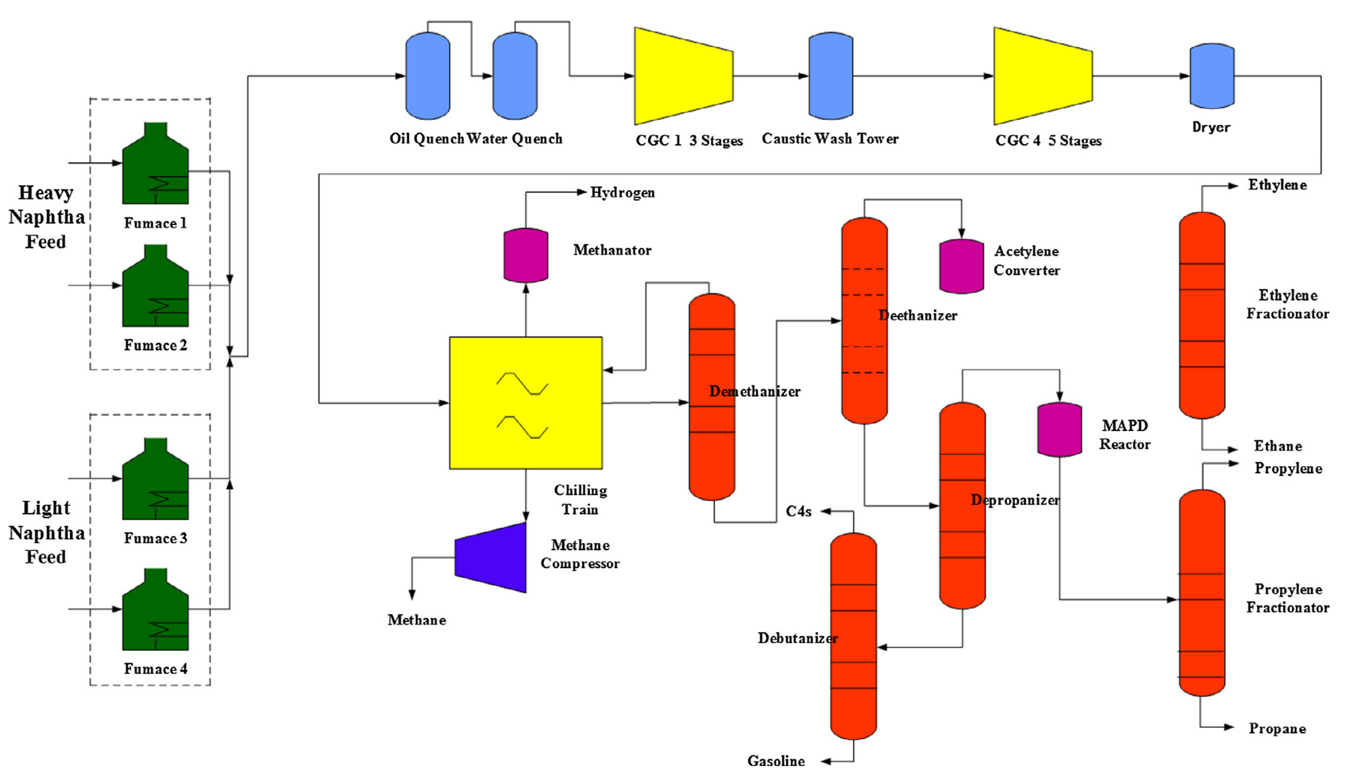

Fig. 2. A typical framework of a typical ethylene plant.

Table 1
Average value of inputs consumption and ethylene outputs of plant 1.

PLANT 1						
Time (year)	Feed (t)	Fuel (GJ/t)	Electricity (GJ/t)	Water (GJ/t)	Steam (GJ/t)	Ethylene (GJ/t)
2011	195740.2458	20.2033	1.1967	2.0558	1.235	62758.3333
2012	201583.2625	20.8283	1.1958	2.0508	1.0542	62552.0833
2013	195580.8192	20.8975	1.2558	2.2392	2.0867	60253.5017

Table 2
Average value of inputs consumption and ethylene outputs of plant 2.

PLANT 2						
Time (year)	Feed (t)	Fuel (GJ/t)	Electricity (GJ/t)	Water (GJ/t)	Steam (GJ/t)	Ethylene (GJ/t)
2011	48392.25	15.8942	1.5783	0.6183	30.71	15326.5833
2012	50252.8333	15.9633	1.535	0.5608	28.5808	17274.8583
2013	44311.6667	16.6233	1.9508	0.8425	28.2783	14526.0833

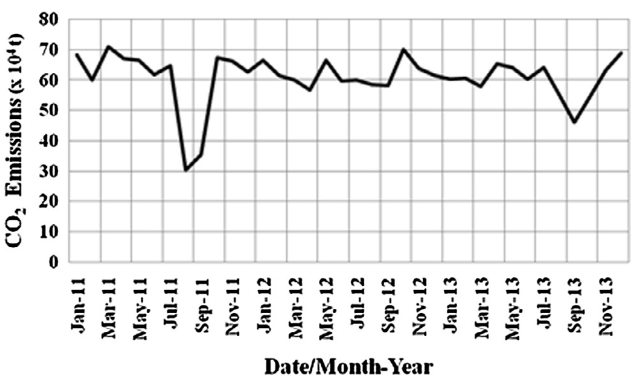

Fig. 3. CO_2 emissions curve of ethylene plant 1.

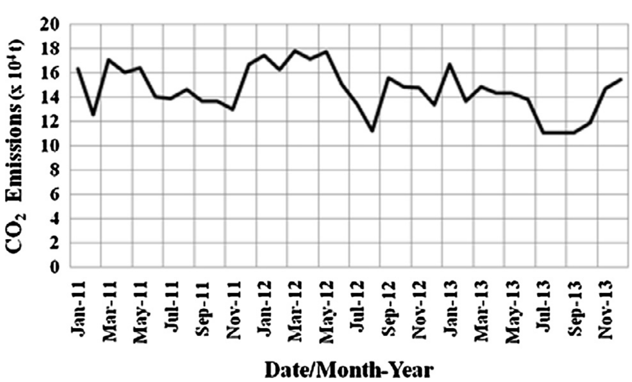

Fig. 4. CO_2 emissions curve of ethylene plant.

Based on the preferred weights and the production data sets of plant 1 and plant 2, we calculate the efficiencies of ethylene production under model 5, and the results as shown in Table 3.

The ethylene production plant 1 and plant 2 are of the different production scales, which are 80 ten-thousands and 20 ten-thousands, respectively. The choice of plants under different production scales contributes to a more comprehensive analysis of ethylene production environmental efficiency. In DEA evaluation theory, particularly application in petrochemical industry, the quantity of DEA efficient DMUs should not more than one-third of the total DMUs, and at this time, the evaluation model is deemed as valid and having great discrimination [35].

As we can see in Table 3, every efficiency variable of the production month in plant 1 and plant 2 is revealed. We have concluded that the quantity of efficiency variables which equals to 1 (DEA effective) in plant 1 are 5, 7, 6, 5 and 5, respectively. Comparing the total 36 DMUs, the DEA effective months account for less more than one-third, i.e. 13.89%, 19.44%, 16.67% and 13.89%, respectively. Similarly plant 2, the quantity of DEA effective indexes of every production month are 4, 3, 12, 4 and 3, which are also conform to the above criteria. The proposed model shows great discrimination in environmental evaluation of ethylene production, and it demonstrates that the proposed model is efficacious. From the performance of efficiency variables, we can easily find that the α_e of plant 2 shows great performance than others, and thus, it illustrate that the electricity of energy inputs of plant 2 is more reasonable than the others.

For a more detailed rationality analysis of individual energy input, we judge the performance of them from the perspective of average. In plant 1, the average efficiency values of the three energy inputs are 0.9265, 0.8117 and 0.8272, evidently the crude material input is more reasonable than the others and the fuel input should be made the largest adjustment. And for plant 2, the values are 0.8284, 0.8538 and 0.8532, respectively, which shows the similar performance. However, the values of the three efficiency indexes are at a low level, and therefore, the energy inputs of plant 2 should be made the same degree of adjustment. In addition, we find that the values of θ, which reflects the performance of carbon dioxide emissions of the DMUs, are very close to the efficiency index ω_o. Due to the inputs are independent in DEA method, so we can easily conclude that the CO_2 emissions are heavily influenced by raw material inputs. What makes this situation is that the consumption of material is a lot more than the other four inputs. And from this point we can also conclude that the more reasonable adjustments for raw material input, the more helpful for carbon dioxide reduction.

In addition, the EPI in the proposed model reflects the environmental performance of the decision making units synthetically. Based on the DEA theory, the DEA inefficient months, i.e. EPI not equal to 1, can be improved by the slacks of inputs and obtained the potential of CO_2 reduction. So to say, we want to get the more DEA inefficient DMUs. From 2011 to 2013, there are 36 ethylene production DMUs, and the quantities of inefficient DMUs of plant 1 and plant 2 are 31 and 33, from which we can see the powerful discrimination of the proposed model. To show the environmental performance of the two ethylene plants intuitively, the radar maps Figs. 5 and 6 reveal the performance of every production month during 2011–2013.

From the radar maps we can easily grasp the overall environmental performance of the two ethylene plants 2011–2013. In the maps, not only the curves of the same year are shown, but also

Table 3
Efficiency results of plant 1 and plant 2.

Date	PALNT 1					PLANT 2				
	α_o	α_f	α_e	θ	EPI	α_o	α_f	α_e	θ	EPI
Jan-11	1	1	1	1	1	0.7538	0.9174	1	0.7539	0.8383
Feb-11	1	1	1	1	1	0.7292	0.6664	0.7041	0.7292	0.7144
Mar-11	1	1	1	1	1	0.7915	0.9898	1	0.7916	0.9041
Apr-11	0.9242	1	1	0.9242	0.9553	0.7659	0.9179	1	0.7660	0.8491
May-11	0.9456	0.8730	0.9454	0.9456	0.9337	0.8020	0.9305	1	0.8021	0.8688
Jun-11	0.9806	0.8161	0.9131	0.9806	0.9414	0.7812	0.8164	0.8832	0.7813	0.8054
Jul-11	0.9256	0.9033	0.8878	0.9256	0.9151	0.7782	0.8050	0.7212	0.7782	0.7723
Aug-11	0.9050	0.4299	0.3487	0.9049	0.7266	0.7659	0.8375	0.8730	0.7659	0.7970
Sep-11	0.8560	0.4748	0.4560	0.8559	0.7212	0.7772	0.7922	0.8208	0.7772	0.7875
Oct-11	0.9709	1	0.9711	0.9710	0.9791	0.7772	0.7922	0.8208	0.7772	0.7875
Nov-11	0.8855	0.8822	0.9009	0.8855	0.8878	0.7664	0.7421	0.8453	0.7664	0.7766
Dec-11	0.9728	0.9733	0.9385	0.9728	0.9667	0.7955	0.9941	1	0.7956	0.8850
Jan-12	0.9246	0.8275	0.9275	0.9246	0.9092	0.9285	0.9940	1	0.9285	0.9678
Feb-12	0.9341	0.7181	0.8608	0.9340	0.8854	0.7909	0.9581	1	0.7910	0.8943
Mar-12	0.9165	0.7043	0.7714	0.9165	0.8555	1	1	1	1	1
Apr-12	0.8636	0.7390	0.7434	0.8636	0.8214	0.8461	0.9975	1	0.8462	0.9342
May-12	1	1	1	1	1	1	1	1	1	1
Jun-12	0.9666	0.9028	0.8384	0.9666	0.9330	0.7708	0.8681	0.9634	0.7708	0.8215
Jul-12	0.8941	0.8481	0.7774	0.8941	0.8655	0.7749	0.7786	0.6764	0.7749	0.7577
Aug-12	0.8929	0.8174	0.7726	0.8929	0.8588	1	0.8805	0.7847	1	0.9762
Sep-12	0.8754	0.7819	0.7782	0.8754	0.8425	0.9802	0.9030	0.8653	0.9801	0.9468
Oct-12	1	1	1	1	1	0.9404	0.9212	1	0.9404	0.9743
Nov-12	0.9267	0.8323	0.8863	0.9267	0.9039	0.9316	0.9506	0.9788	0.9316	0.9432
Dec-12	0.9562	0.7356	0.8366	0.9562	0.8984	1	1	1	1	1
Jan-13	0.9468	0.7155	0.7804	0.9468	0.8788	0.7781	0.9727	0.9727	0.7781	0.8452
Feb-13	0.9425	0.7309	0.8213	0.9425	0.8859	0.7856	0.8005	0.7649	0.7856	0.7843
Mar-13	0.8882	0.8226	0.7623	0.8882	0.8547	0.8057	0.8913	0.8711	0.8058	0.8316
Apr-13	0.9327	0.7627	0.8674	0.9327	0.8930	0.8317	0.8913	0.8711	0.8317	0.8486
May-13	0.9093	0.7667	0.8411	0.9093	0.8736	0.7986	0.8565	0.7963	0.7986	0.8077
Jun-13	0.8698	0.8060	0.8155	0.8698	0.8495	0.7891	0.7917	0.7238	0.7891	0.7778
Jul-13	0.9396	0.7413	0.8247	0.9395	0.8863	0.7968	0.6577	0.4814	0.7968	0.7171
Aug-13	0.8184	0.6824	0.5751	0.8184	0.7522	0.7968	0.6577	0.4814	0.7968	0.7171
Sep-13	0.8345	0.5814	0.4967	0.8344	0.7320	0.7968	0.6577	0.4814	0.7968	0.7171
Oct-13	0.8491	0.7098	0.6484	0.8491	0.7900	0.8024	0.6137	0.6203	0.8023	0.7385
Nov-13	0.9436	0.7786	0.8419	0.9435	0.8982	0.8026	0.7282	0.8659	0.8026	0.8018
Dec-13	0.9612	0.8642	0.9506	0.9612	0.9434	0.7899	0.7631	0.8488	0.7899	0.7961
Average	0.9265	0.8117	0.8272	0.9264	0.8900	0.8284	0.8538	0.8532	0.8284	0.8440

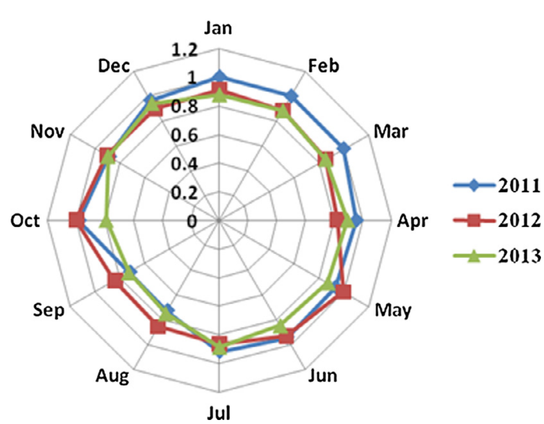

Fig. 5. EPI radar map of plant 1 during 2011–2013.

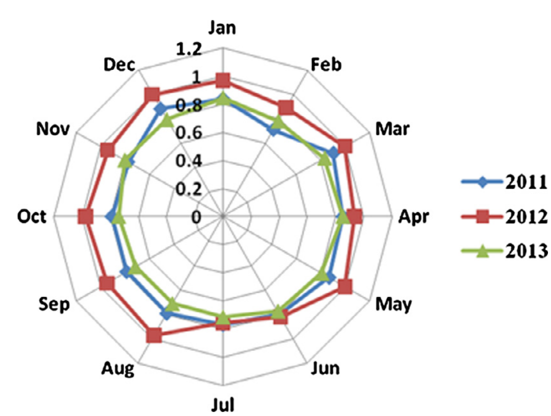

Fig. 6. EPI radar map of plant 2 during 2011–2013.

the same month of different year, more valuable is that we can observe the annual performance together, which contributes to the comparison among the three years.

3.3. Energy savings and CO_2 emissions reduction

Based the above efficiency results, through the adjustment by slacks, the inefficient DMUs can be improved and reach DEA efficient. In this sub-section, we will discuss the potential of energy savings and CO_2 emissions reduction of the DEA inefficient production months.

The energy savings and CO_2 emissions reduction of all inefficient production months can be obtained by using Eqs. (6)–(9). To show the potential intuitively, we draw the area figures to provide a visual description of the potential of abatement, and as shown in Figs. 7 and 8. In the figures, the area in positive direction of the longitudinal axis means the energy savings, due to the savings of fuel, electricity, water and steam are much less than the raw material, so these four inputs are not seen clearly. The area of vertical axis in the negative direction reflects the potential of CO_2 reduction.

Note that in Fig. 7, the potential of energy savings and CO_2 reduction changes dramatically in ethylene plant 1. The largest

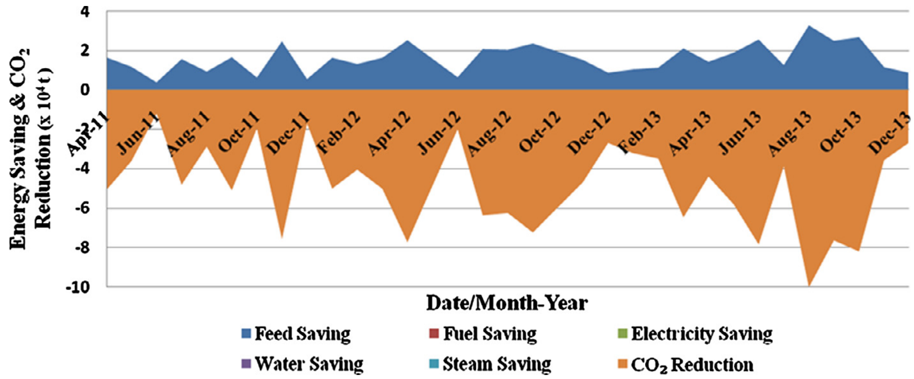

Fig. 7. The potential of energy savings and CO_2 reduction of plant 1.

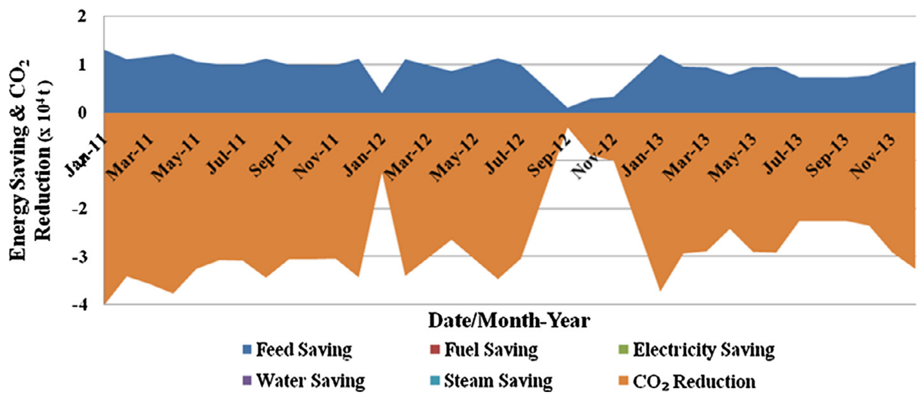

Fig. 8. The potential of energy savings and CO_2 reduction of plant 2.

reduction of CO_2 is 100328.4581 t in Aug-13, and we can see from Table 3, the efficiency value of Aug-13 is lower than the other months. Accordingly, the month is also the best performance of energy savings, which is 32682.95187 t the inputs totally. The least potential of energy savings and carbon dioxide abatement is Jun-11, 3903.124779 t and 11981.70789 t, respectively. While in Fig. 8 the plant 2 shows different performance, the potential of energy savings and CO_2 of every inefficient month changes relatively steady except several months. Most of the potential of energy savings and exhaust gas reduction values of the inefficient months around 10,000 t and 30,000 t, respectively. Here we can focus on analyzing the several lower months. The lowest potential of plant 2 in environmental performance is Sep-12, the total energy saving is 1013.4377 t and CO_2 emissions reduction can be only 3111.527466 t. What makes this situation is the efficiency indexes are perform very high, which are 0.9802, 0.9030, 0.8653, 0.9801 and 0.9468 for feed, fuel, electricity, water and steam. Likewise, the other three better months, Jan-12, Oct-12 and Nov-12, perform the better environmental efficiency. So the plant 2 can follow the product approach of the four months to achieve better environmental performance.

Above all we have discussed, the two ethylene plants have great potential for energy savings and emissions abatement. And we can also provide the production guidance for the environmental efficiency improvement based on the efficiency results obtained from the proposed model, which contribute to environmental protection.

4. Discussion

First, the energy and environmental efficiency evaluation method of petrochemical industries based on the improved environmental DEA is proposed. The proposed method synthesizes the environmental efficiency value of energy inputs and undesirable outputs to help us grasp the energy and environmental comprehensive performance of DMUs.

Second, this proposed method is used to evaluate and analyze the energy and environmental performance of ethylene plants in the petrochemical industry. The potential of energy saving and CO_2 emissions reduction are obtained by the improved environmental DEA to improve the energy and environmental efficiency of the ethylene production. Meanwhile, it is reasonable to figure out efficiency indices of energy inputs, desirable and undesirable outputs. Moreover, the operation guidance for energy saving and CO_2 emissions abatement is provided.

Third, the proposed performance analysis modeling method is applied to estimate the potential of energy saving and CO_2 emissions reduction and improve the energy and environmental efficiency. However, the performance of desirable outputs is not considered. Therefore, we will improve our model that the desirable output is considered in the efficiency analysis to pursue a balance between inputs reduction and economic benefit.

5. Conclusions

This paper proposed an environmental DEA approach to evaluate energy and environmental efficiency of petrochemical industry. And we take ethylene production for example to illustrate the potential of energy saving and CO_2 emissions reduction. We divide the five inputs into energy inputs and non-energy inputs. The ethylene is considered as desirable outputs and the CO_2 emission is deemed as undesirable outputs. The application on ethylene real production demonstrates the validity of the proposed model. It can be applied in the potential evaluation of energy saving and carbon dioxide abatement in petrochemical industry.

As the results obtained, we can draw some conclusions. First, most of the production months of ethylene plants are DEA inefficient, and the performer should adjust product method to improve the environmental performance, which can also save energy inputs. Second, the carbon dioxide emissions have a great relationship with raw material inputs in petrochemical, which is the key factor to improve the environmental performance, and the production policy maker should take this into consideration. The last but not the least, petrochemical production under different scales has different potential of energy savings. The larger scales plants contain the less potential to improve compared the smaller scales.

In our future studies, we will take the structure of ethylene inputs into account, which may reveal much more potential of energy savings and pollutant emissions reduction through energy structure adjustment. Furthermore, we will improve our method considering the desirable output in the efficiency analysis to pursue a balance between inputs reduction and economic benefit. These issues may attract some interesting research in future.

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