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Energy and environment efficiency analysis based on an improved environment DEA cross-model: Case study of complex chemical processes

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HIGHLIGHTS

- An improved environment DEA cross-model method is proposed.
- Energy and environment efficiency analysis framework of complex chemical processes is obtained.
- This proposed method is efficient in energy-saving and emission reduction of complex chemical processes.

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ABSTRACT

The complex chemical process is a high pollution and high energy consumption industrial process. Therefore, it is very important to analyze and evaluate the energy and environment efficiency of the complex chemical process. Data Envelopment Analysis (DEA) is used to evaluate the relative effectiveness of decision-making units (DMUs). However, the traditional DEA method usually cannot genuinely distinguish the effective and inefficient DMU due to its extreme or unreasonable weight distribution of input and output variables. Therefore, this paper proposes an energy and environment efficiency analysis method based on an improved environment DEA cross-model (DEACM) method. The inputs of the complex chemical process are divided into energy and non-energy inputs. Meanwhile, the outputs are divided into desirable and undesirable outputs. And then the energy and environment performance index (EEPI) based on the cross evaluation is used to represent the overall performance of each DMU. Moreover, the improvement direction of energy-saving and carbon emission reduction of each inefficiency DMU is quantitatively obtained based on the self-evaluation model of the improved environment DEACM. The results show that the improved environment DEACM method has a better effective discrimination than the original DEA method by analyzing the energy and environment efficiency of the ethylene production process in complex chemical processes, and it can obtain the potential of energy-saving and carbon emission reduction of ethylene plants, especially the improvement direction of inefficient DMUs to improve energy efficiency and reduce carbon emission.

1. Introduction

The main reason for global warming caused by human activities is the widespread use of fossil fuels (such as coal and oil) in the last decades, and it has emitted a large number of greenhouse gases into the atmosphere. In all greenhouse gases, carbon dioxide has the highest contribution rate, the longest survival period, and is the major factor that leads to climate change and global warming [1]. The petrochemical industry is an important industry related to national production and life. Meanwhile, the petrochemical industry is also a high pollution and high carbon emissions industry. Therefore, analyzing the energy and environment efficiency of the complex petrochemical industry is imperative.

In many environment efficiency evaluation methods, data envelopment analysis (DEA) method is widely used as a nonparametric programming method because of its very important practical significance and economic background, especially in the field of environment performance evaluation of enterprise micro-level [2]. The DEA method is an evaluation method based on the concept of relative efficiency and linear programming. The efficiency of the decision-making unit (DMU) in the DEA method is defined as the ratio of the weighted sum of the output variables to the weighted sum of the input variables. The efficiency index of the DMU is independent of the unit selection of inputs and outputs, so there is no necessary for dimensionless data processing of the DEA model. The DEA method also

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ruled out a lot of subjective factors because it does not need any weight assumption on the inputs and outputs. Therefore, the DEA method has a unique advantage in the efficiency evaluation of multiple inputs and multiple outputs. However, the traditional DEA method usually cannot genuinely distinguish the effective and inefficient DMUs due to its extreme or unreasonable weight distribution of input and output variables. In this paper, an improved environment DEA cross-model (DEACM) method is proposed. The inputs of a complex chemical process are divided into energy inputs and non-energy inputs. Meanwhile, the outputs are divided into desirable outputs and undesirable outputs. First, the improvement direction of energy utilization efficiency and carbon emission reduction of all inefficiency DMUs are obtained based on the self-evaluation model of the improved environment DEACM. Second, the energy and environment performance index (EEPI) based on the cross evaluation is used to represent the overall performance of each DMU. This proposed method has good efficiency discrimination ability, and it can also give the improvement direction of the inefficient DMU by quantitatively calculation. Moreover, the proposed method is applied to analyze the energy and environment efficiency of the complex ethylene production process. The results show that the proposed method can obtain the potential of energy-saving and emission reduction of ethylene plants, especially the improvement direction of all inefficient DMUs to improve energy utilization efficiency and reduce carbon emission.

The rest of the paper is organized as follows. Section 2 is the literature review of energy and environment efficiency analysis. Section 3 introduces the environment DEA cross-model to calculate the energy-saving and emission reduction potential. The improved environment DEACM is applied to analyze the energy and environment efficiency of the ethylene production process in the complex chemical process to prove the effectiveness of the proposed method in Section 4. Discussion and Conclusion are in s 5 and 6, respectively.

2. Literature review

The DEA method was first proposed by operational researchers Charnes, Cooper and Rhodes in 1978 [3]. Since then, the DEA method has been widely used to analyze the energy and environment efficiency. Xie et al. assessed the electric power industry in BRIC nations (China, India, Russia and Brazil) by adopting the environmental Malmquist index based on a SBM-DEA (slack based measure data envelopment analysis) model. And they found that fuel structure change and technological progress were the main driving forces to promote dynamic environmental efficiency [4]. Zhu et al. studied DEA combined with life-cycle environmental impacts of products for eco-efficiency evaluation to examine the eco-efficiencies of ten comparable pesticides. And they found out that the network DEA method can distinguish differences in the eco-efficiency of products at the different stages [5]. Cui et al. applied a virtual frontier DEA to evaluate transportation carbon efficiencies, and analyzed the cases from 15 countries during the period of 2003–2010. The results indicated that compared with the technology factor and management factor, the influencing degree of a structure factor is relatively small [6]. Wu et al. proposed a DEA-based approach to allocate China's national CO_2 emissions and energy intensity reduction targets over Chinese provincial industrial sectors. The results showed that the most effective allocation of the national reduction target requires most of the 30 regional industrial to reduce CO_2 emission and energy intensity, while a few can increase or maintain their 2010 levels [7]. Meng et al. conducted a comprehensive survey of empirical studies published in 2006–2015 on China's regional EE & CE assessment by using DEA-type models. The main features used in previous studies were identified, and then the methodological framework for deriving the EE & CE indicators as well as six widely used DEA models were introduced [8]. Li et al. applied a three-stage DEA model to measure the effects of government measures on green productivity growth and introduced an improved Malmquist–Luenberger productivity index to measure the green productivity growth of China's manufacturing sector during the 11-th Five-Year Period. They proved China's energy-saving policies and measures, such as closure and elimination of obsolete production capacity, and reduction of over-capacity is important for green development [9]. Hernández-Sancho et al. applied a non-radial DEA method to analyze energy efficiency indices for the sampling of wastewater treatment plants in Spain, and got the potential savings in economic terms and carbon emission to provide the guidance for the efficiency improvement [10]. Wei et al. investigated the energy efficiency of China's iron and steel sector from 1994 to 2003 by using Malmquist Index Decomposition [11]. Sueyoshi and Yang et al. studied the DEA window analysis for environment assessment in a dynamic time shift to evaluate the operational, environment and both-unified performance of coal-fired power plants [12–14]. In addition to the above applications, the DEA has been applied in the complex chemical process. Azadeh et al. used the fuzzy neural algorithm to evaluate the environment performance [15] and eco-efficiency [16] of large petrochemical plants, which is the first intelligent algorithm to evaluate the environment performance. Zhu et al. evaluated the energy efficiency by combining the DEA-CCR model and principal component analysis (PCA) to reduce the amount of data in petrochemical production processes [17]. In order to estimate the eco-efficiency of the industrial sector, Charmondusit provided a basic framework for the environment efficiency assessment of the Thai petrochemical plant and enable public participation in the discussion on branch developments and contributions to national trends [18]. Geng et al. used the Malmquist production index method based on DEACM and fuzzy DEACM to study the performance efficiency of Chinese ethylene plants [19]. Geng et al. proposes an efficiency analysis method based on FDEACM (fuzzy DEA cross-model) with fuzzy data. And the proposed method has better objectivity and resolving power for the decision-making [20]. However, the numbers of inputs and outputs indicators and the number of samples have a significant effect on the results of the DEA analysis [21,22]. Han et al. proposed a new energy analysis framework for the petrochemical industry process based on the DEA Comprehensive Interpretation Structure Model (ISM). Based on the partial correlation coefficient method, the ISM method was proposed to find out the main factors and basic causes of the energy consumption of ethylene production. This method can overcome the difficulties of different weight assessment and decision-making [23].

All the above methods for the environment efficiency evaluation do not achieve the purpose of emission reduction through energy-saving, and there is no quantitative analysis of energy-saving and emission reduction in these methods. In this paper, an energy and efficiency evaluation method based on an improved environment DEACM is proposed. This method classifies the inputs and outputs of complex chemical processes, estimates the carbon emissions, and combines the DEACM to obtain the efficiency of each plant. This proposed method can also use the relaxation coefficients and energy efficiencies to quantitatively calculate the energy-saving and emissionreduction potential, and provide the guidance for energy-saving and carbon emission reduction of ineffective DMUs.

3. The environment DEA cross-model

3.1. DEA cross-model

Each object of the DEA research problem is called a DMU. Assuming that there are n DMUs, and the data form of each DMU is:

$$DMU_i = [x_i \quad y_i] \quad i = 1,2,...,n$$

Wherein $x_i = [x_{1i},x_{2i},...,x_{mi}]^T, y_i = [y_{1i},y_{2i},...,y_{si}]^T$ are the m inputs and s outputs of i-th DMU, respectively.

Set $v = [v_1,v_2,...,v_m]^T, u = [u_1,u_2,...,u_s]^T$ are the weight vector of inputs and outputs, respectively. And then the efficiency value of DMU is $E_{ii} = \frac{y_i^T u}{x_i^T v}$.

The aim of CCR model of the DEA method is solving the optimal solution in Eq. (1).

$$\max y_i^T u = E_{ii}$$
$$s.\ t. \begin{cases} y_l^T u - x_l^T v \leqslant 0, & l = 1,2\ldots,n \\ x_i^T v = 1 \\ u \geqslant 0, & v \geqslant 0 \end{cases} \tag{1}$$

In order to calculate and apply easily, the relaxation variable s^+ and the residual variable s^- are introduced, and the above inequality constraint model becomes an equality constraint model as shown in Eq. (2).

$$\min[\theta - \varepsilon(e_1^T s^- + e_2^T s^+)]$$
$$s.\ t. \begin{cases} \sum_{i=1}^{n} \lambda_i x_{ji} + s^- = \theta x_{ji}, & j = 1,2,\ldots,m \\ \sum_{i=1}^{n} \lambda_i y_{ri} - s^+ = y_{ri}, & r = 1,2,\ldots,s \\ \lambda_i \geqslant 0, & i = 1,2,\ldots,n \\ s^- \geqslant 0, & s^+ \geqslant 0 \end{cases} \tag{2}$$

Wherein, ε is a minimum parameter and θ is the relative efficiency value. If the optimal target value θ^* of the linear programming is 1, and the optimal solution conform the inequality $\lambda_j * > 0$, $s_j^+ * > 0$, $s_j^- * > 0$, we consider the DMU_j is valid.

The solution of Eq. (2) is the u, v that make the i-th DMU get the maximum efficiency value (called the self-evaluation efficiency value), which is denoted as u_i^*, v_i^*, The most favorable input and output weights of every DMU are used in solving the efficiency of this DMU to get the maximum value of E_{ii}. In this process, the input and output variables which are conducive to DMU's efficiency are often given a very high weight. And these variables which aren't conducive to DMU's efficiency are often given a very small weight [4]. This may lead to overly optimistic evaluations of the efficiency of every DMU due to the extreme weight assignments. Meanwhile, more than one-third of the DMUs' efficiency values can reach 1, so that the effective and ineffective DMUs cannot be distinguished [24,25].

In order to solve this problem, the DEA cross-model is introduced. The DEA cross evaluation is a new method as a sorting tool for multi-criteria decision making [26–28]. The basic principle of the DEA cross-model is using the optimal weight assignment ui^* and vi^* of the i-th DMU to calculate the efficiency of other DMUs. In some cases, the optimal weight assignment u_i^*, v_i^* of the i-th DMU is not unique. We use the confrontation model, i.e. using the weight assignment that makes other DMUs getting the lowest efficiency value (other-evaluation efficiency value), to calculate the efficiency of other DMUs. The DEA cross-model is shown in Eq. (3).

$$\min y_k^T u$$
$$s.\ t. \begin{cases} y_k^T u - x_k^T v \leqslant 0, & l = 1,2\ldots,n \\ y_i^T u = E_{ii} x_i^T v \\ x_k^T v = 1 \\ u \geqslant 0, & v \geqslant 0 \end{cases} \tag{3}$$

The efficiency of other DMUs calculated by using the optimal solution u_{ik}^*, v_{ik}^* of Eq. (3) is shown in Eq. (4).

$$E_{ik} = \frac{y_k^T u_{ik}^*}{x_k^T v_{ik}^*} \tag{4}$$

Hence, every DMU has n efficiency evaluation values, including one self-evaluation efficiency value and n-1 other-evaluation efficiency values. We can get the n-dimensional efficiency value matrix as shown in Eq. (5). The final efficiency value (called average cross evaluation efficiency) of the i-th DMU can be calculated by Eq. (6).

$$E = \begin{pmatrix} E_{11} & E_{12} & \cdots & E_{1n} \\ E_{21} & E_{22} & \cdots & E_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ E_{n1} & E_{n2} & \cdots & E_{nn} \end{pmatrix} \tag{5}$$

$$e_i = \frac{1}{n} \sum_{k=1}^{n} E_{ki} \tag{6}$$

3.2. Environment DEA cross-model

The resources and energy consumption in petrochemical industry process can be divided into energy inputs and non-energy inputs. Energy inputs will produce carbon emissions, such as electricity, feed, fuel, water, and steam. Other non-carbon emissions resources are called non-energy inputs, so the non-energy inputs cannot be considered in energy efficiency evaluation [20,29]. In practice, carbon emissions cannot be measured directly [30], so we use the Eq. (7) to estimate it, i.e. each energy input is multiplied by its carbon dioxide emission factor [31].

$$C_j = \sum_{i=1}^{G} (X_{ij} \times F_i) \tag{7}$$

Wherein Cj represents the carbon dioxide emission value of the j-th DMU, and X_{ij} is the i-th energy input consumption of the j-th DMU [20]. F_i is the carbon dioxide emission coefficient of the i-th energy input, and G is the number of energy inputs. Common carbon dioxide emission coefficients are shown in Table 1 [32].

The environment efficiency evaluation needs to take the efficiency of every energy input into account. In order to obtain the comprehensive efficiency of energy consumption and carbon emissions, the normalized weight proportional to the carbon emission coefficient is introduced, and the weight of each energy input is given by Eq. (8).

$$\omega_g = F_g/(F_1 + F_2 + \cdots + F_G) \tag{8}$$

Wherein ω_g represents the weight. The energy-environment performance index is defined as EEPI to represent the energy and environment comprehensive efficiency. The EEPI can be calculated by Eq. (9):

$$EEPI_i = \frac{1}{2}(\omega_1 E\theta_{1i} + \omega_2 E\theta_{2i} + \cdots + \omega_G E\theta_{Gi} + E\theta_{ci}) \tag{9}$$

$EEPI_i$ represents the comprehensive efficiency of i-th DMU. $E\theta_{1i}$ is the first energy input's the average cross-evaluation efficiency of the decision i-th DMU, $E\theta_{ci}$ is the average cross-evaluation efficiency of carbon emission.

Every $E\theta$ in Eq. (9) is the average cross evaluation efficiency. In order to obtain the average efficiency, we need to calculate these self-evaluation efficiency values and other-evaluation efficiency values. The self-evaluation efficiency value can be calculated by the improved model in Eq. (10) which is based on Eq. (2).

In Eq. (10), θ_{1i} θ_{2i}, etc. are the energy inputs' self-evaluation efficiency values of i-th DMU. θ_{ci} is the self-evaluation efficiency values of carbon emission. M is the number of the non-energy input, X is the inputs' consumption, i, j is the DMU mark, s is the relaxation coefficient,

Table 1
Common carbon dioxide emission.

Energy	Carbon dioxide emission	Energy	Carbon dioxide emission
Raw coal	2.07	Kerosene	3.08
Cleaned coal	2.49	Diesel	3.16
Slime, Middlings	0.89	Refinery dry gas	2.65
Briquette	2.02	Liquefied petroleum gas	3.17
Coal Briquette total	2.23	Other coke products	3.04
Coke	3.04	Other petroleum products	2.95
Crude Oil	3.07	Natural gas	21.84
Fuel oil	3.24	Coke oven gas	7.71
Gasoline	3	Other coal gas	5.92

Y, C are the chemical production yield and the carbon dioxide emissions estimation, respectively.

$$EEPI_i = \min\left[\tfrac{1}{2}(\omega_1\theta_{1i} + \omega_2\theta_{2i}+\cdots+\omega_G\theta_{Gi} + \theta_{ci})-\varepsilon(e_1^T s_{1i}^- + e_2^T s_{2i}^-+\cdots +e_G^T s_{Gi}^+)\right]$$

$$s.\ t.\begin{cases}\sum_{j=1}^{n}\lambda_j X_{1j} + s_{1i}^- = \theta_{1i}X_{1i}\\ \sum_{j=1}^{n}\lambda_j X_{2j} + s_{2i}^- = \theta_{2i}X_{2i}\\ \vdots\\ \sum_{j=1}^{n}\lambda_j X_{Gj} + s_{Gi}^- = \theta_{Gi}X_{Gi}\\ \sum_{j=1}^{n}\lambda_j X_{(G+1)j} + s_{(G+1)i}^- = X_{(G+1)i}\\ \vdots\\ \sum_{j=1}^{n}\lambda_j X_{(G+M)j} + s_{(G+M)i}^- = X_{(G+M)i}\\ \sum_{j=1}^{n}\lambda_j Y_j - s_{yi}^+ = Y_i\\ \sum_{j=1}^{n}\lambda_j C_j = \theta_{ci}C_i\\ i,j = 1,2,\ldots,n\\ \lambda_j,s_i^-,s_{yi}^+,\theta_i,\theta_{ci} \geqslant 0\end{cases}\tag{10}$$

We not only can get the self-evaluation efficiencies of the energy input and the carbon emission by Eq. (10), but also can calculate the relaxation coefficients and the optimal weight assignment. Taking these results into Eq. (11) which is based on Eq. (3), and combining Eqs. (4) and (6), we can get the average crossevaluation efficiencies of each energy input and the carbon emission. Finally, we can calculate the comprehensive efficiencies of every DMU by Eqs. (8) and (9).

$$\begin{gathered}\min(\omega_1X_{1k},\omega_2X_{2k},\ldots,\omega_GX_{Gk},C_k)^Tu\\ s.\ t.\begin{cases}y_l^Tu - x_l^Tv \leqslant 0, & l = 1,2,\ldots,n\\ y_i^Tu = E_{ii}x_i^Tv\\ x_k^Tv = 1\\ u \geqslant 0, & v \geqslant 0\end{cases}\end{gathered}\tag{11}$$

It can be seen from Eq. (10) that changing the relaxation coefficient of each energy input can maximize the efficiency in Eq. (9), so the energy-saving potential of each energy input can be tapped by the relaxation coefficient. The energy-savings and carbon dioxide emission reduction are determined by their efficiency values and the relaxation coefficient in Eq. (10). As shown in Eq. (12). Wherein S_{gi} is the energy-saving potential of the g-th energy input of i-th DMU, and Cr is the potential of carbon emission reduction.

$$\begin{aligned}S_{gi} &= (1-\theta_{gi})X_{gi} + s_{gi}^-\\ Cr &= (1-\theta_{ci})C_i\end{aligned}\tag{12}$$

In summary, the main process of the environment DEACM method is shown in Fig. 1 and the following explanation:

Step 1: Data pretreatment. In order to estimate the carbon emissions, we distinguish energy inputs and non-energy inputs, desired outputs and undesired outputs based on data sources.

Step 2: Calculate the efficiency values. First, we solve the energy input utilization, carbon emission self-evaluation efficiency values and the relaxation coefficient of every DMU by Eq. (10) to get the cross evaluation efficiency. Second, we calculate the average efficiency of the cross evaluation model by Eqs. (4)–(6).

Step 3: Analyze the energy-saving and emissionreduction potential. We calculate the energy-saving and emission reduction potential of each DMU by Eq. (12) to evaluate the energy and environmental efficiency, and provide the improvement direction of inefficient DMUs.

4. Case study: energy and environment efficiency analysis of complex chemical processes

In this section, the proposed method was applied to analyze the energy and environment efficiency of Chinese ethylene plants' complex chemical processes. There are 7 kinds of technologies for ethylene production in China [33]. More than 20 ethylene production plants have been selected to evaluate EEPIs in the past ten years, and the efficiency values of each energy input and carbon dioxide emission efficiency values are analyzed. Meanwhile, the potential of energy-saving and emission reduction were calculated.

4.1. Data analysis

Ethylene production processes include cracking and separation. The cracking phase is the main core of the entire ethylene plant. Most energy consumption of the ethylene plant comes from the cracking section [23]. It requires a lot of fuel to provide heat to promote the cracker when the cracker is running. At the same time, the quench boiler is producing a large amount of steam by recovering waste heat. In order to achieve the best effect of hydrocarbon in a short period of time and reduce coking, the steam should be injected when supplying hydrocarbons to the cracking plant [34]. The crack structure consists of two radiation segments and a common convection section [35] as shown in Fig. 2.

In addition to feed, the main inputs of ethylene production include: water (recycled water, industrial water, boiler water), steam (ultra-high pressure steam, high- pressure steam, low-pressure steam), fuel (fuel gas, light oil, heavy oil), electricity, N_2 and compressed gases. Since the content of N_2 and compressed gas consumption is very low, they are not considered in the ethylene energy efficiency analysis process. Energy consumption constitute makes up the input of ethylene production energy efficiency evaluation, while the output is the ethylene production [23].

We choose two petrochemical plants in China as the object of analysis. The data include the ethylene yield and the energy consumption and the raw material of two years as shown in Figs. 3 and 4, respectively. For the sake of uniform calculation, the consumptions of fuel, electricity, and steam were generally converted to the amount in unit of GJ [23] based on the standard SH/T3110-2001 [32], DB 37/751-2007 [36] and GB/T 2589-2008 [37], while the feed, ethylene production, carbon emissions were converted to the amount in unit of Ton (t). Set the number of DMUs with ethylene plants as 24.

The carbon dioxide emission is mainly related to the consumption of feed, oil, electricity, that is, these three inputs are called energy inputs. Water and steams are called non-energy inputs. According to Table.1, the emission coefficient of feed, fuel and power are taken 3.07, 3.24 and 3.56. We can estimate the amount of carbon dioxide emissions though the data of the plants based on Eq. (7). And then we can get the weights by Eq. (8). The compositions and proportions of EEPIs calculated by Eq. (9) are shown in Fig. 5.

The self-evaluation efficiency values of every DMU's energy-inputs and desirable-outputs can be obtained by taking the inputs consumption data, the ethylene yield and the carbon emission into the model in Eq. (10). Due to the shortcomings of the DEA method, nearly one-third of the self-evaluation efficiency values reaches 1, and more than half are above 0.9. We cannot distinguish the effective and ineffective DMUs according to the unreasonable results. However, we calculate the efficiencies of energy inputs, carbon emission, and the relaxation coefficient of each DMU by Eqs. (6), (8), (9), (11). The energy-saving and emission reduction potential can be obtained by Eq. (12).

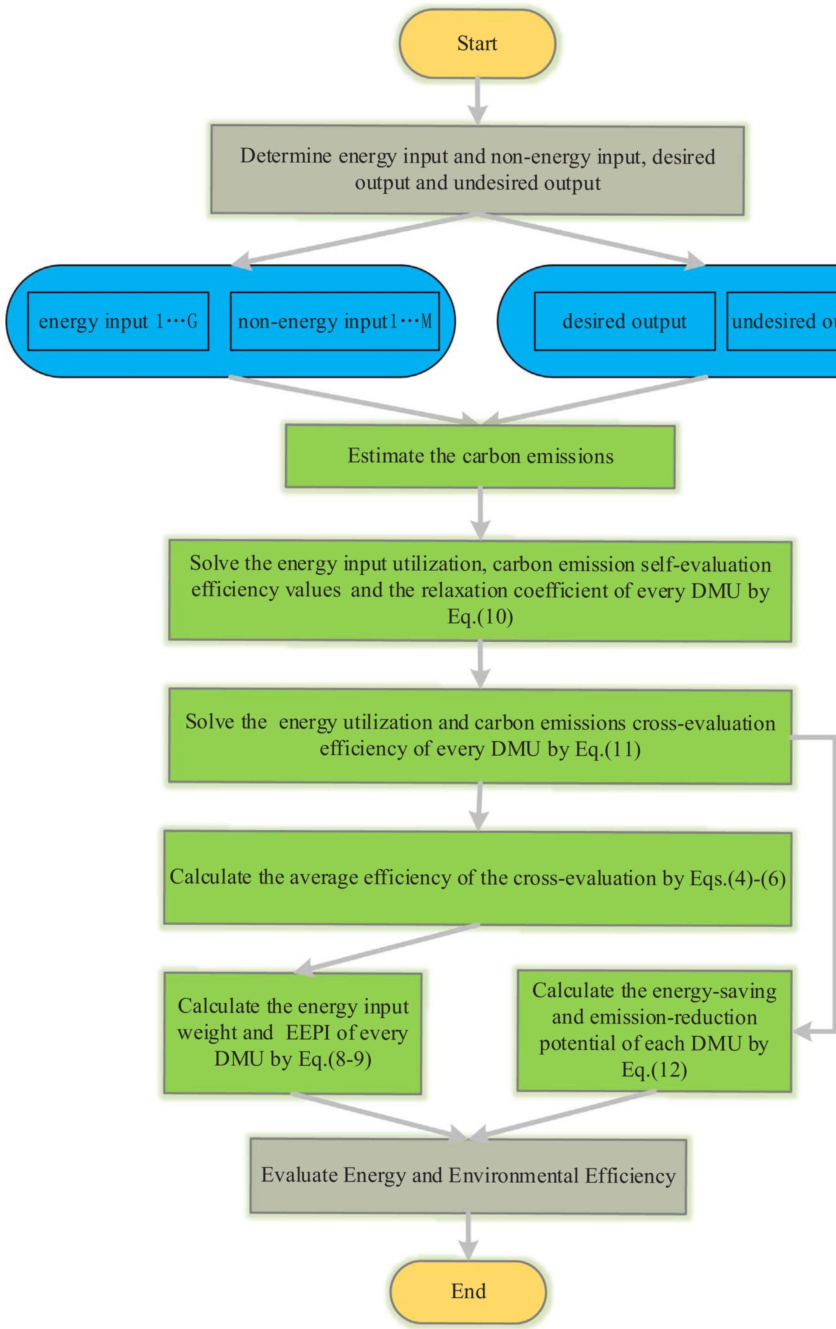

Fig. 1. The process of the environment DEACM method.

4.2. The result analysis of the treatment

The carbon dioxide estimated value is obtained by analyzing the different ethylene plants with different scales based on the environment DEA cross-model method as shown in Fig. 6. And the carbon emission of plant 1 is significantly higher than that of plant 2 due to the different scale.

Meanwhile, all the self-evaluation efficiency of each DMU can be obtained by using Eq. (10), and the energy-saving and emission reduction potential can be calculated by Eq. (12). In order to intuitively reflect the potential of energy-saving and emission reduction, we draw curves as shown in Figs. 7–14. These figures show the energy-savings of each energy input and carbon dioxide emission reduction. Compared them with original consumption and emissions, the percentage curves are also shown in these figures. The histogram corresponds to the left ordinate and the line chart corresponds to the right ordinate. The energy-saving and emission reduction potential of each project are consistent with the change trend of efficiency values.

The least feed-saving potential of plant 1 is 0 GJ in May, June, October 2012 and December 2013, and the most is 17,521 GJ in August 2013. The least fuel-saving potential is 0 GJ in May, October 2012 and December 2013, and the most is 10 GJ in September 2013. The least electricity-saving potential is 0 GJ in May, October 2012 and December 2013, and the most is 0.744 GJ in September 2013. The smallest potential for carbon emission reduction is 0 t in May, June, October 2012 and December 2013, and the most is 53,819 t in August 2013. It can be seen that the self-evaluation performance in May, June, October 2012, and December 2013 of plant 1 are the best, and the corresponding self-evaluation efficiencies reach 1, so their potential is 0. Other DMUs whose self-evaluation efficiencies do not reach 1 have the improvement potential, especially in August and September 2013, and their potential is the largest.

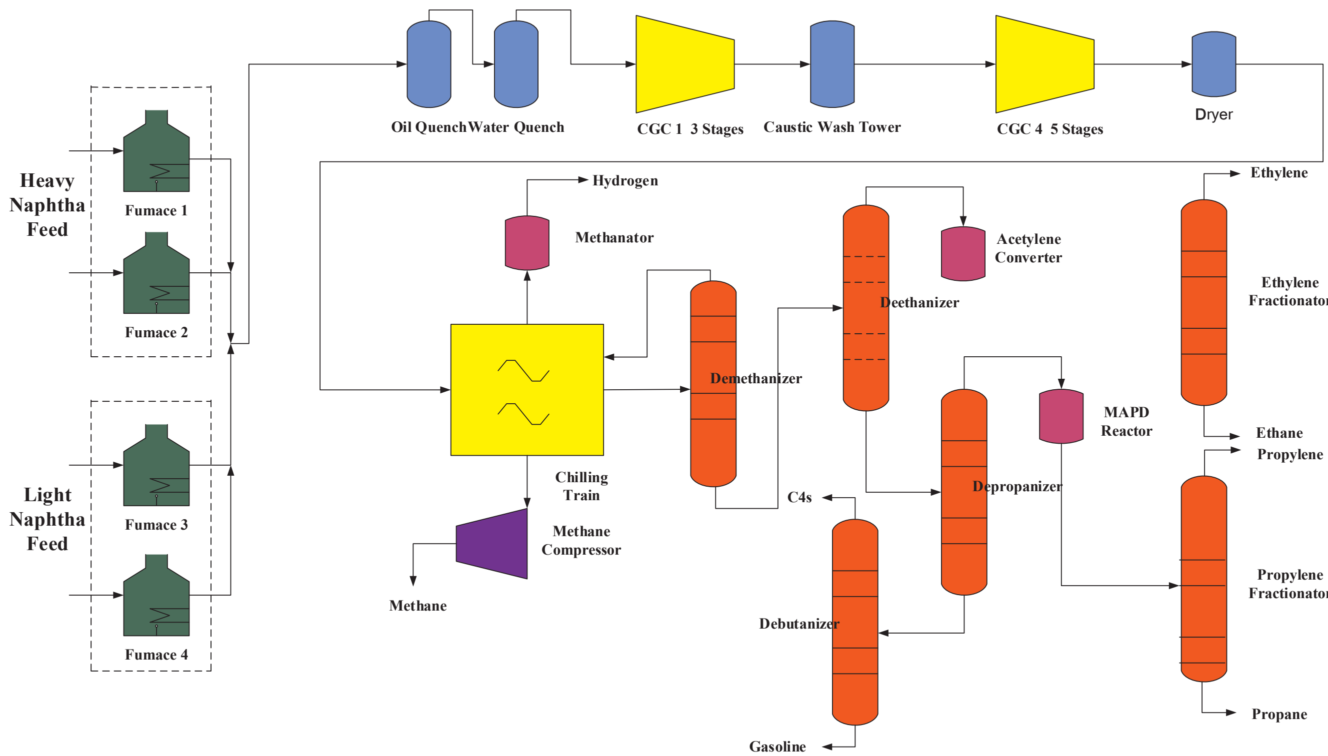

Fig. 2. A brief flow chart of a typical ethylene plant.

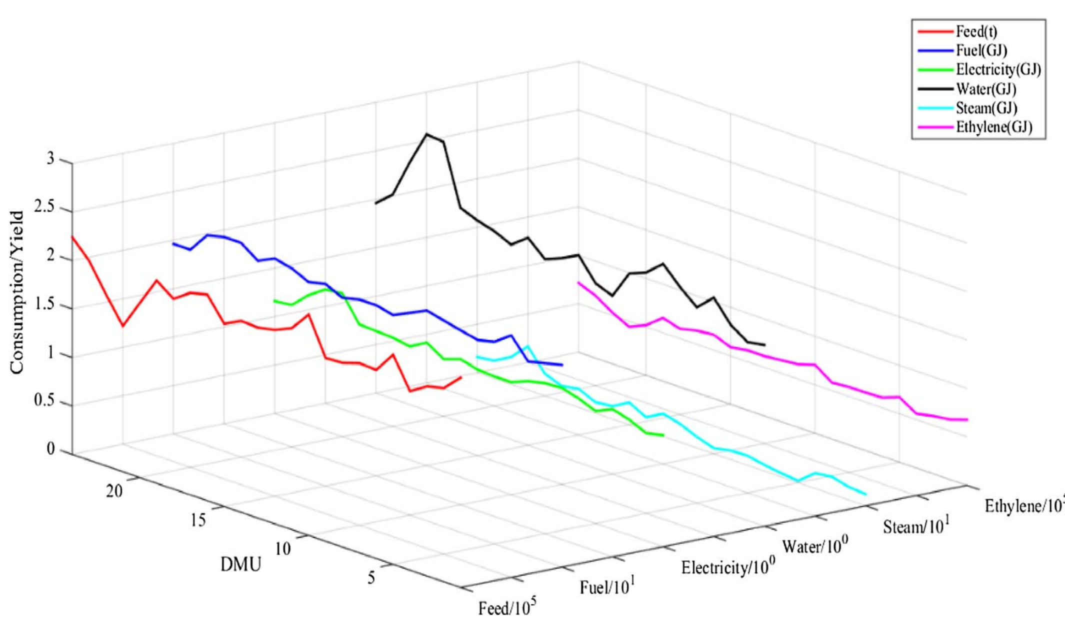

Fig. 3. Energy consumption and ethylene yield of plant 1.

The least feed-saving potential of plant 2 is 0 GJ in May, August, December 2012, and the most is 12,129 GJ in January 2013. The least fuel-saving potential is 0 GJ in March, May, December 2012, and the most is 7.1 GJ in October 2013. The least electricity-saving potential is 0 GJ in January, February, March, April, October 2012, and the most is 1.219 GJ in September 2013. The smallest potential for carbon emission reduction is 0 t in March, May, August, December 2012, and the most is 37,240 t in January 2013. It can be seen that the effective DMU of plant 2 is more in self-evaluation, and the corresponding self-evaluation efficiencies reach 1, so their potential is 0. Other DMUs whose self-evaluation efficiencies do not reach 1 have the improvement potential, especially in January 2013, and their potential is the largest.

In the self-evaluation of the DEA method, there are nearly one third of DMUs' efficiency reach 1. Although we can get the potential of energy-saving and emission reduction, we cannot distinguish the effective and ineffective DMUs and cannot find the benchmark-DMUs. Thus the results of the cross-evaluation are shown in Table.2, wherein the $E\theta o$, $E\theta f$, $E\theta e$, $E\theta c$ represent the efficiency of feed, fuel, electricity and carbon emission, respectively. As a result of using the DEA cross-model and plenty of DMUs, there is no efficiency value reach 1, which reflects the good efficiency distinction ability of the DEA cross-model.

The more intuitional contrast of every DMU's EEPI is shown in

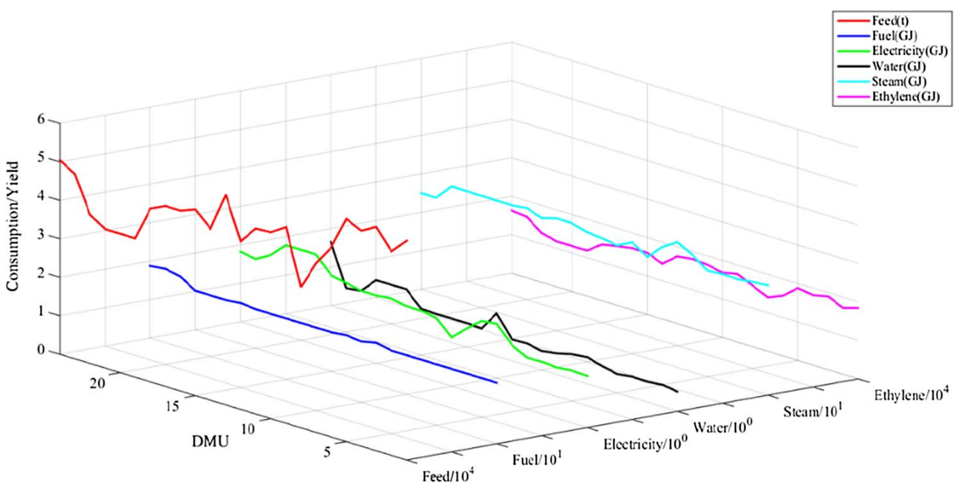

Fig. 4. Energy consumption and ethylene yield of plant 2.

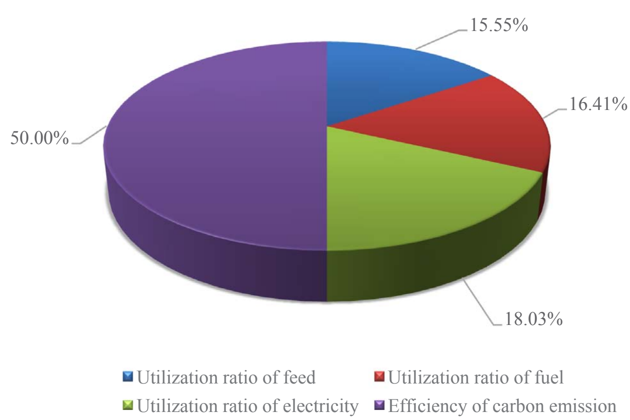

Fig. 5. The compositions of EEPI.

Fig. 15. It can be seen from the radar figure that the EEPI of plant 1 is higher than that of plant 2 overall. The EEPI of plant 2 in January 2013 and December 2013 are the lowest, which was affected by the increase of feed consumption and other energy inputs' consumption remained the same. Under the cross evaluation, the best DMUs of the two plants are June 2012 of palnt1 and October 2012 of plant 2. The energy utilization, the carbon emission efficiency and the EEPI of the two DMUs all reached the highest value. The two DMUs can be used as benchmarks to improve the production of those ineffective DMUs.

After we get the benchmark-DMUs and take the January 2013 of plant 2 as an improvement example. The consumption of feed, fuel, electricity, water and steams is 54,657 t, 15.86 GJ 1.72 GJ, 1.11 GJ, 27.99 GJ, respectively. And the ethylene yield and the carbon emission are 17,490 t and 167,854 t, respectively. Compared with the benchmark-DMU of plant 2, the DMU's consumption of feed, fuel, electricity and yield are all similar to the benchmark, but the consumption of water and steams are twice as much as that of the benchmark, so that the efficiency is relatively low and the carbon emission is relatively high. And then the inefficient DMU can reference the usage method of water and steams of the benchmark-DMU to improve its efficiency.

From the view of the average value of the two plants as shown in radar Fig. 16, we can see that the efficiency of plant 2 is lower than that of plant 1, especially the feed utilization efficiency, the carbon emission efficiency and the EEPI. The fuel and power utilization efficiency are similar. In summary, the efficiencies of plant 1 are higher than that of plant 2.

It can be seen from Figs. 7–14 that the ratio of energy-saving and emission reduction is in upward trend on the whole, which means that the efficiencies of 2013 is lower compared with that in 2012. It is necessary to tap the potential of energy-saving and emission reduction. The optimal efficiency values of the above two plants do not reach 1 under the environment DEACM, so they all have certain improvement potential. These efficiencies, energy-saving results and benchmark-DMUs will provide the guidance on the ethylene production improvement.

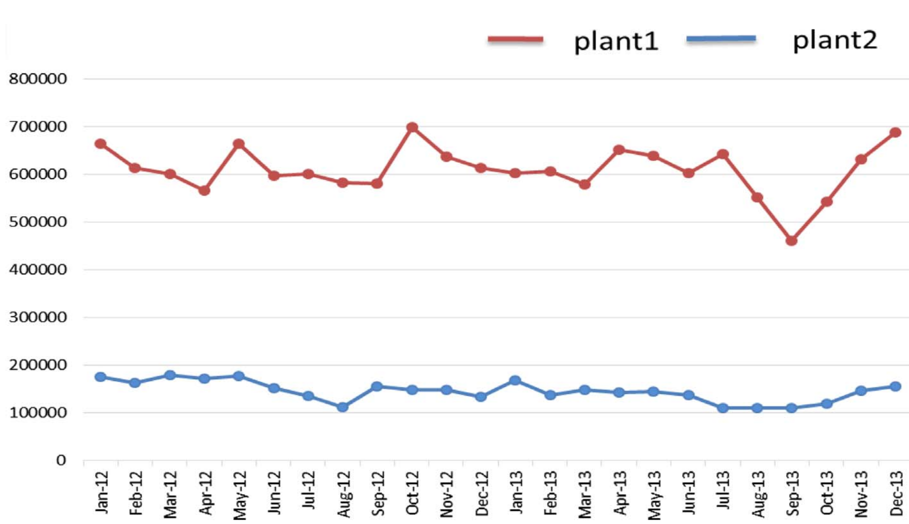

Fig. 6. Estimates of carbon emission.

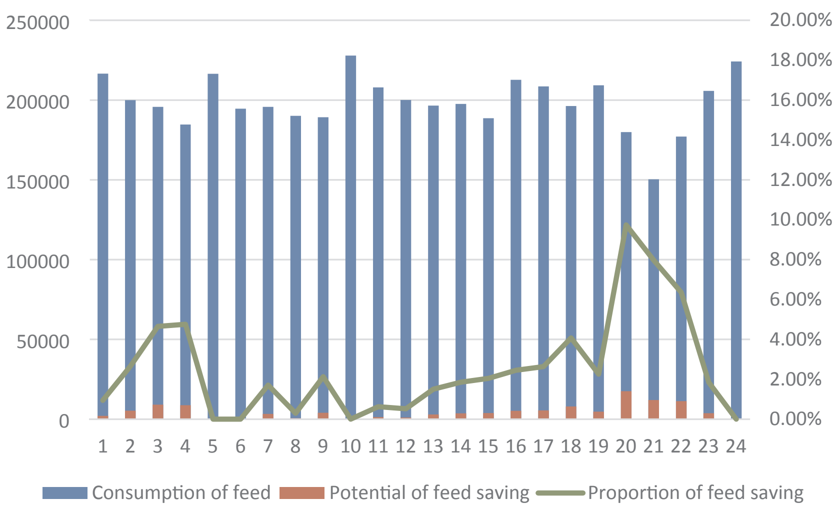

Fig. 7. Potential of feed saving of plant 1.

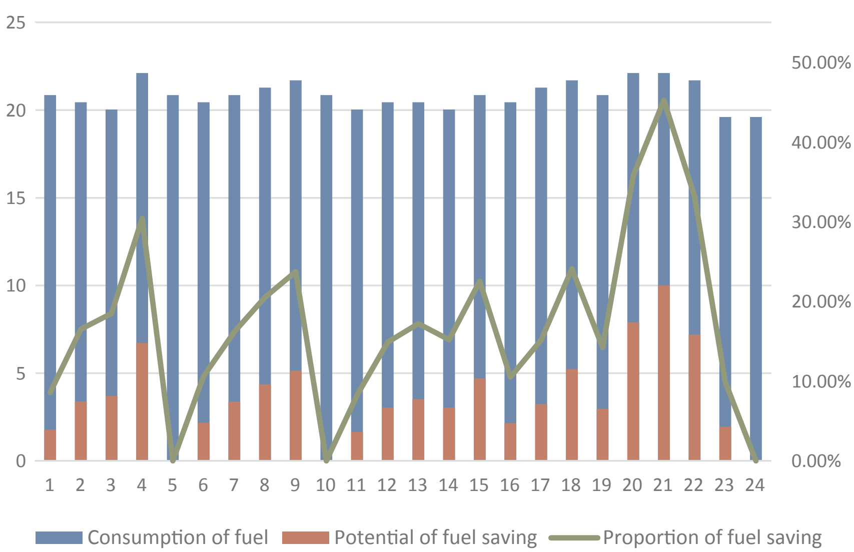

Fig. 8. Potential of fuel saving of plant 1.

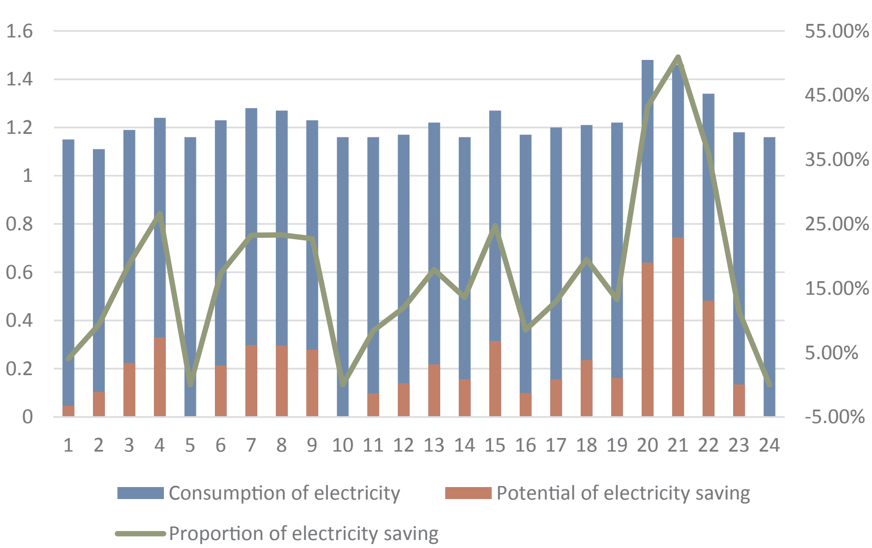

Fig. 9. Potential of electricity saving of plant 1.

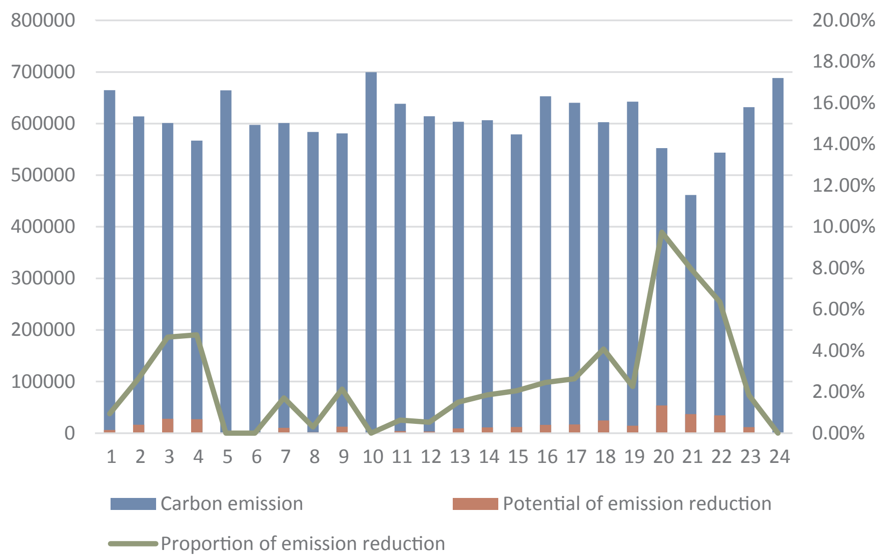

Fig. 10. Potential of emission reduction of plant 1.

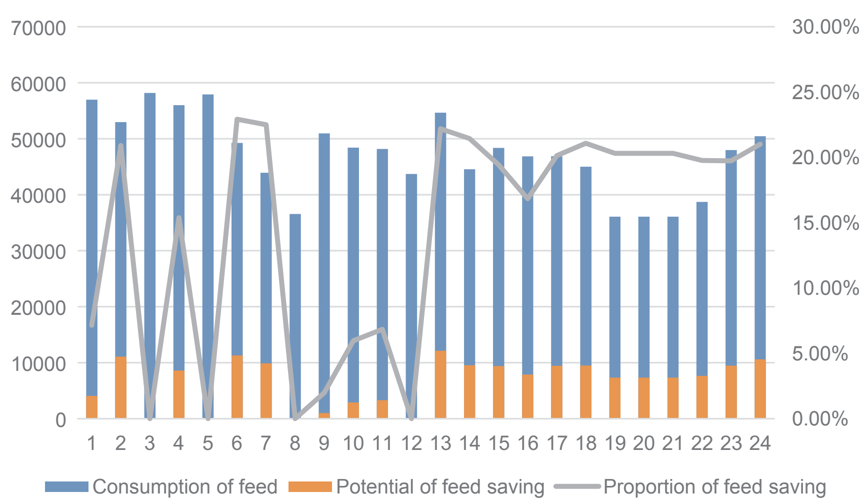

Fig. 11. Potential of feed saving of plant 2.

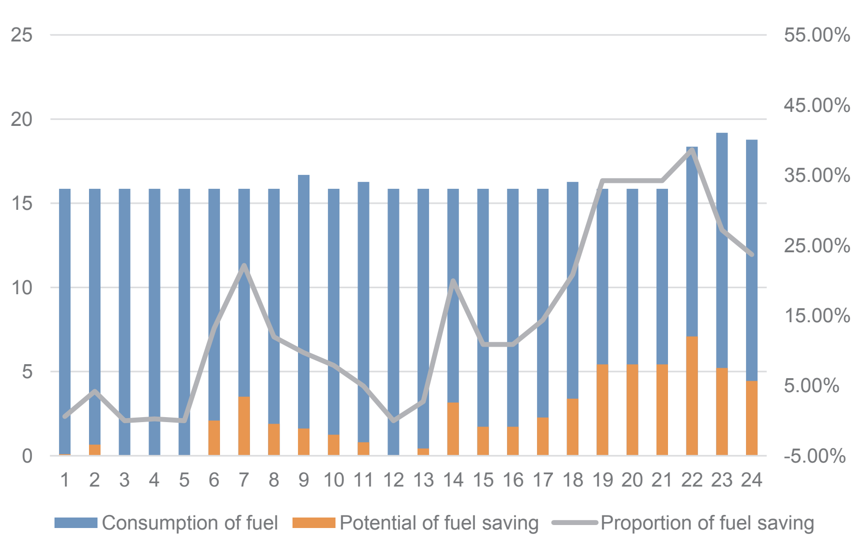

Fig. 12. Potential of fuel saving of plant 2.

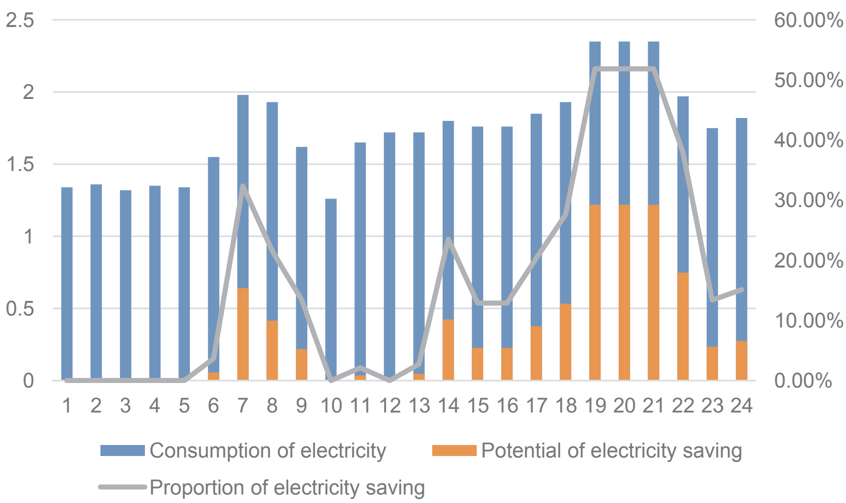

Fig. 13. Potential of electricity saving of plant 2.

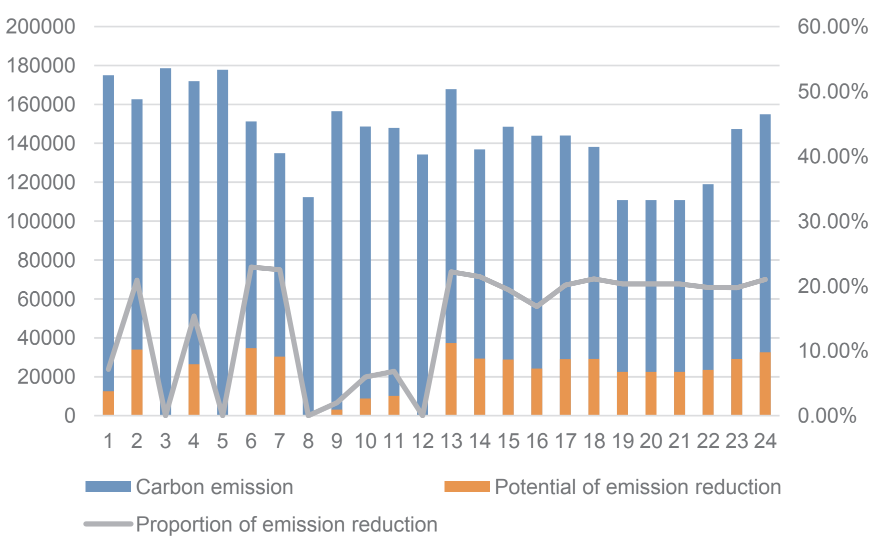

Fig. 14. Potential of emission reduction of plant 2.

5. Discussion

In this paper, the environment DEACM method is proposed to evaluate the energy and environment performance of the petrochemical industry. The method combines the energy and carbon emission efficiency to obtain the comprehensive efficiency indicators of each DMU.

The energy efficiency, the carbon emission efficiency and the EEPIs of each ethylene production plant are calculated and compared by using the proposed method to tap the energy-saving and carbon emission reduction potential.

The proposed method can provide the quantitative guidance for the production of energy-saving and emission reduction. However, the deficiency is that the inputs values are all translated from the initial data with having a high dimension. So the deficiency would lead to the direction of energy-saving and emission reduction is not clear enough. Therefore, we will analyze the high-dimension initial data by principal component analysis (PCA) in the later work. Meanwhile, we only take the efficiency of undesired outputs into account. In the future, the efficiency value of the desired outputs can be taken into account to achieve the balance between the production and the environment protection.

6. Conclusion

This paper proposed an improved environment DEACM method and divided the inputs into energy inputs and non-energy inputs and the outputs into desired outputs and undesired outputs to evaluate the energy and environment performance of complex chemical processes. The efficiency of every DMU is analyzed by taking the ethylene production plant as an example, and the potential of energy-saving and carbon emission reduction are tapped. Firstly, all plants under the different scales do not reach the optimal efficiency value, and they all have a certain energy-saving and emission reduction potential. Secondly, the carbon emissions are most affected by the raw material consumption, so saving raw materials is the key to reduce carbon emissions. Finally, the case study of energy and environment efficiency analysis of ethylene production plants proved the validity and rationality of the environment DEACM method. The evaluation results show that the proposed model has a better efficiency distinguish ability compared with the DEA method which may get one third of the DMUs' efficiency values reach 1. Meanwhile, we quantitatively calculate the savings potential value and find the benchmark of energy-saving and emission reduction by comparing the EEPI of every DMU to point out the improvement direction of the inefficiency DMU.

Table 2
Efficiency results of each DMU.

Time	Plant 1					Plant 2				
	EθO	Eθf	Eθe	Eθc	EEPI	Eθo	Eθf	Eθe	Eθc	EEPI
Jan-12	0.8363	0.7101	0.7097	0.8363	0.7927	0.7169	0.7240	0.7386	0.7169	0.7220
Feb-12	0.8777	0.7435	0.7431	0.8777	0.8314	0.7412	0.7477	0.7613	0.7412	0.7459
Mar-12	0.8626	0.7292	0.7288	0.8626	0.8166	0.7052	0.7123	0.7269	0.7052	0.7103
Apr-12	0.8553	0.7202	0.7188	0.8553	0.8085	0.7233	0.7303	0.7450	0.7233	0.7283
May-12	0.8853	0.7575	0.7561	0.8852	0.8410	0.7114	0.7185	0.7331	0.7114	0.7165
Jun-12	0.9089	0.7714	0.7689	0.9088	0.8611	0.7405	0.7443	0.7530	0.7405	0.7433
Jul-12	0.8660	0.7327	0.7302	0.8660	0.8196	0.6986	0.6952	0.6950	0.6986	0.6974
Aug-12	0.8741	0.7379	0.7358	0.8741	0.8268	0.7569	0.7499	0.7468	0.7569	0.7539
Sep-12	0.8830	0.7457	0.7437	0.8830	0.8353	0.7376	0.7406	0.7499	0.7376	0.7403
Oct-12	0.8287	0.7068	0.7057	0.8287	0.7865	0.7836	0.7890	0.8011	0.7836	0.7877
Nov-12	0.8659	0.7349	0.7342	0.8659	0.8207	0.7531	0.7553	0.7626	0.7531	0.7552
Dec-12	0.8383	0.7084	0.7080	0.8382	0.7934	0.7722	0.7718	0.7752	0.7722	0.7727
Jan-13	0.8275	0.6987	0.6984	0.8275	0.7831	0.5495	0.5498	0.5523	0.5495	0.5501
Feb-13	0.8809	0.7457	0.7451	0.8809	0.8342	0.7483	0.7476	0.7500	0.7483	0.7485
Mar-13	0.8311	0.7003	0.6994	0.8311	0.7859	0.7284	0.7301	0.7351	0.7284	0.7299
Apr-13	0.8386	0.7113	0.7108	0.8386	0.7946	0.7442	0.7453	0.7498	0.7442	0.7454
May-13	0.8474	0.7179	0.7170	0.8474	0.8026	0.7258	0.7258	0.7287	0.7258	0.7263
Jun-13	0.8310	0.7010	0.7005	0.8310	0.7861	0.7264	0.7244	0.7254	0.7264	0.7259
Jul-13	0.8199	0.6936	0.6930	0.8199	0.7763	0.6216	0.6120	0.6047	0.6216	0.6170
Aug-13	0.7665	0.6427	0.6404	0.7665	0.7234	0.6216	0.6120	0.6047	0.6216	0.6170
Sep-13	0.7487	0.6259	0.6247	0.7487	0.7062	0.6216	0.6120	0.6047	0.6216	0.6170
Oct-13	0.7994	0.6711	0.6700	0.7994	0.7550	0.7193	0.7128	0.7132	0.7193	0.7171
Nov-13	0.8319	0.7040	0.7037	0.8318	0.7877	0.7074	0.7056	0.7128	0.7074	0.7081
Dec-13	0.7964	0.6762	0.6760	0.7964	0.7549	0.4448	0.4409	0.4397	0.4448	0.4432
Average	0.8417	0.7119	0.7109	0.8417	0.7968	0.7000	0.6999	0.7046	0.7000	0.7008

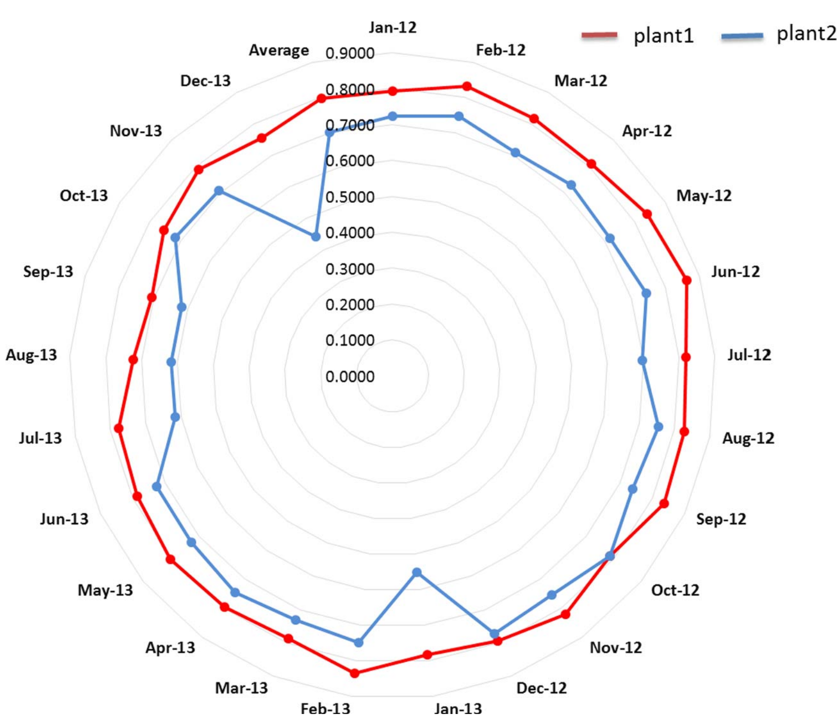

Fig. 15. EEPI radar map of plant 1 and plant 2.

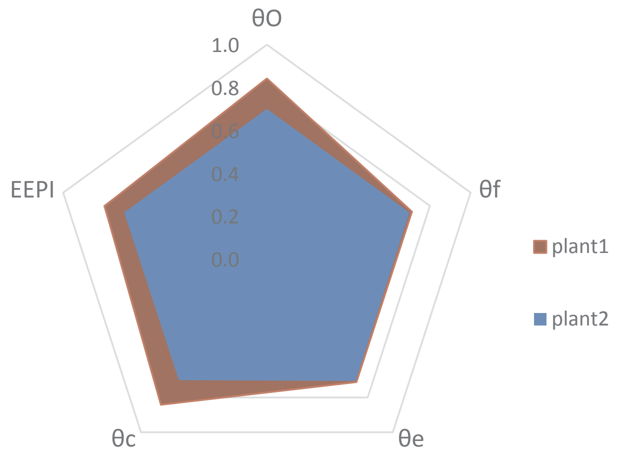

Fig. 16. Average EEPI contrast radar map of plant 1 and plant 2.

In our future studies, we will analyze the high-dimension initial data by principal component analysis. Moreover, we will take the production structures or technologies into consideration to clarify the improvement direction of energy-saving and emission reduction and achieve the balance between the environment protection and the production.

Acknowledgments

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