Energy efficiency evaluation of ethylene industries based on DEA models

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Abstract: Data envelopment analysis (DEA) have been widely applied in the energy efficiency evaluation of process systems. However, the DEA has many different kinds of models and characteristics, which leads to different discrimination power in different application fields. Particularly in efficiency evaluation of petrochemical systems, the proper choice of DEA model makes great difference in improving the sensibility and accuracy of the result, which contributes to guiding production and improving the energy efficiency. This paper proposes a more appropriate DEA model to evaluate the production efficiency of ethylene plants, which can provide better guidance of ethylene production and energy saving. The empirical results demonstrate the effectiveness and universality of the DEA-CCR model application in energy efficiency evaluation of ethylene plants.

Key Words: Data envelopment analysis, energy efficiency evaluation, ethylene plants

1 Introduction

Petrochemical industry is a typical process industry, producing products continuously or semi-continuously and consuming high energy, which leading to generating heavy pollution. The total energy consumption of petrochemical industry accounts for about 20% of national total industrial energy consumption [1].As a result, petrochemical industry brings a lot of pressure to saving energy and protecting the environment. The difference of average energy consumption of petrochemical industry between China and worldwide advanced level ranges from 5% to 15% [1]. It is clear that petrochemical industry of China falls behind international level a lot. There is much room in improvement and application for energy efficiency optimization of petrochemical production process of our country.

As the pioneer of petrochemical industry, ethylene industry production capacity has become an important symbol of national industrial level. The petrochemical companies in China produced 9475kt/a ethylene in 2012. Ethylene production needs 579.59kg standard oil per ton [2]. Ethylene output of oil companies in China is 5110kt/a, which requires 628.6kg standard oil [3]. The energy efficiency of China is far below than that of developed countries, while energy consumption is the main operating costs in ethylene production [4].Therefore, analyzing the energy efficiency of ethylene production is of great significance.

Nowadays, data envelopment analysis (DEA) has been widely applied in energy efficiency analysis of industrial production, and DEA models have been extended and improved under different demands. But there still exists some disadvantages. For example, the results of the DEA can be affected by input/output indexes and quantity of samples, and too many evaluation standards can make the quantity of decision-making units whose efficiency value is 1 exceeds one third of the sum of units, which will lead to inaccurate evaluation differentiation[5]. In the production efficiency evaluation of process industry, Zhu et al. [6] reduced the dimension of data in petrochemical production by combining DEA-CCR model and Principal Component Analysis (PCA). Geng et al. [7] [8] 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. In the study of DEA Models classification, Ma [9] analyzed and summarized common DEA models systematically and put forward four most representative basic models of DEA: CCR, BCC, FG and ST, which are named after the author who proposed.

In the past, the energy efficiency of petrochemical industry was evaluated mainly by the improving and expanding DEA-CCR.CCR is a kind of the four classic DEA models. While the other three DEA basic models are researched and applied rarely. Comparing with four DEA basic models in the energy efficiency evaluation of petrochemical industries, we can decide the most suitable one for energy efficiency evaluation of the petrochemical industry, and there are practical significance and reference value for the extension and improvement of the DEA models in the energy efficiency evaluation of the petrochemical industry in the future. This paper takes ethylene industry production for instance, combining with the basic principles of DEA models to compare the performance of four DEA basic models, and then, we find out the proper DEA model which is more suitable for the ethylene production energy efficiency evaluation. This research is helpful to guide ethylene production and improve energy efficiency.

2 Data Envelopment Analysis

Data Envelopment Analysis (DEA) was proposed by the Charnes and Cooper in 1978 to evaluate the effectiveness of the decision-making unit. DEA has formed a relatively complete model system at present, and plays an important role in decision-making and evaluation of many areas. DEA

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model extends the efficiency concept of single-input / single-output to Decision Making Units (DMU) relatively effective evaluation system, which is of multi-input / multiple-output. DMU can be an industrial system or a production cell. A number of production factors make up the "input", while the "output" is consist of a number of products. These products are the results of decisions produced by DMU, so the DMU is the object that DEA models evaluate.

CCR model, BCC model, FG model and ST model are the four most representative models of DEA model system in the DEA theory system [9].

2.1 DEA-CCR

CCR model is the basic model in relative efficiency evaluation system of fixed- scale income patterns [9]:

Assuming that evaluation system has n decision units, m inputs and s outputs indexes, the j-th input and output index vectors of DMU respectively are $X_j=(x_{1j},x_{2j},\cdots,x_{mj})^T>0$ and $Y_j=(y_{1j},y_{2j},\cdots,y_{mj})^T>0$, j = 1,2, ... ,n. The linear programming of CCR model is expressed as:

$$D_{CCR}=\begin{cases} \min\{\theta\} \\ s.t.\quad \sum_{j=1}^{n} X_j\lambda_j + s_j^{+} = \theta X_{j0} \\ \sum_{j=1}^{n} Y_j\lambda_j - s_j^{-} = Y_{j0} \\ \lambda_j, s_j^{+}, s_j^{-} \ge 0, j=1,2,...,n \end{cases} \tag{1}$$

In model (1), 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 (D_{CCR}) is 1, and the optimal solution $\lambda_j^*> 0$, $s_j^{+*}> 0$, $s_j^{-*}> 0$, we call DMU_j as DEA effective [10].

2.2 DEA-BCC

BCC Model was proposed by Banker, Charnes and Cooper in 1984. This model is the basic model of relative efficiency evaluation whose income scale is variable. It was put forward under the circumstance that production possible sets of some problems were not convex cone. We did not concern the circumstance that production possible sets satisfied cone [9].

Supposing that evaluation system has n decision units, m inputs and s outputs indexes, the input and output index vectors of j-th DMU respectively are $X_j=(x_{1j},x_{2j},\cdots,x_{mj})^T>0$ and $Y_j=(y_{1j}, y_{2j},\cdots,y_{mj})^T>0$, j = 1,2, ..., n. This model is expressed as:

$$D_{BCC}=\begin{cases} \min\{\theta\} \\ s.t.\quad \sum_{j=1}^{n} X_j\lambda_j + s_j^{+} = \theta X_{j0} \\ \sum_{j=1}^{n} Y_j\lambda_j - s_j^{-} = Y_{j0} \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j, s_j^{+}, s_j^{-} \ge 0, j=1,2,...,n \end{cases} \tag{2}$$

In model (2), 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 (D_{BCC}) is 1, and the optimal solution $\lambda_j^*> 0$, $s_j^{+*}> 0$, $s_j^{-*}> 0$, we call DMU_j as DEA effective [11].

2.3 DEA-FG

While researching scale merit by using non-parametric methods, Fare and Grosskopf proposed the new DEA model in 1985, which is now called FG model. This model is based on the technology assumptions of non-increasing returns to scale [9]. The mathematical model as follows:

$$D_{FG}=\begin{cases} \min\{\theta\} \\ s.t.\quad \sum_{j=1}^{n} X_j\lambda_j + s_j^{+} = \theta X_{j0} \\ \sum_{j=1}^{n} Y_j\lambda_j - s_j^{-} = Y_j \\ \sum_{j=1}^{n} \lambda_j + h^{+} = 1 \\ \lambda_j, s_j^{+}, s_j^{-}, h^{+} \ge 0, j=1,2,...,n \end{cases} \tag{3}$$

In model (3), 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^+, s_j^- and h^+ are slack variables. λ_j, θ, s_j^+, s_j^- and h^+ 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 (D_{FG}) is 1, and the optimal solution $\lambda_j^*>0$, $s_j^{+*}>0$, $s_j^{-*}>0$, $h^+>0$, we call DMU_j as DEA effective [12].

2.4 DEA-ST

In 1990, Seiford and Thrall presented ST model, which is based on the technology assumptions of non-decreasing returns to scale. The production possible sets are based on the axiom system: triviality, convexity, invalidity, expansion and minimum axiom [9]. The mathematical tabular of this model is:

$$D_{ST} = \begin{cases} \min\{\theta\} \\ s.t. \quad \sum_{j=1}^{n} X_j \lambda_j + s_j^{+} = \theta X_{j0} \\ \qquad \sum_{j=1}^{n} Y_j \lambda_j - s_j^{-} = Y_{j0} \\ \qquad \sum_{j=1}^{n} \lambda_j - h^{-} = 1 \\ \qquad \lambda_j, s_j^{+}, s_j^{-}, h^{-} \geq 0, j = 1,2,...,n \end{cases} \quad (4)$$

In model (4), 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^+, s_j^- and h^- are slack variables. λ_j, θ, s_j^+, s_j^-, h^- 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 (D_{ST}) θ^* is 1, the optimal solution $\lambda_j^* > 0$, $s_j^{+*}>0$, $s_j^{-*}>0$, $h^->0$, we call DMU_j as DEA effective [13].

3 Ethylene Data Description

Different ethylene plants in ethylene production choose different calculation methods. 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 [16] [17].

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. While the majority energy consumption of the ethylene plants comes from the cracking section. 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 cracking 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 is consist of two radiant section and a common convection section, as shown in Figure 1:

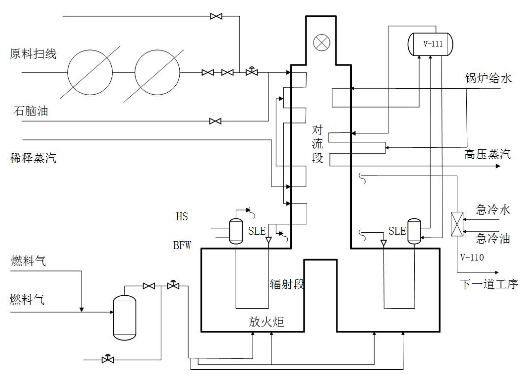

Figure 1: Flow chart of cracking furnace crafts

We can know from the figure that the energy types in main factors of the ethylene productivity 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. The 'TTL' is abbreviation for 'total'. While N2 and compressed gas consumption are very low, so we did not take them into consideration of ethylene energy efficiency analysis process [14]. 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).And energy consumption makes up the input of ethylene production energy efficiency evaluation ,while the output is ethylene production[15].

This paper converts the consumption data of ethylene plants which based on conversion relationship showed in Table 3.0.2 and Table 3.0.3 in <Calculation Method for Energy Consumption in Petrochemical Engineering Design> (SH/T3110-2001). It uniformly converts the measurement units of the fuel, steam, water, and electricity in the consumption relevant parameters to GJ [18].

4 Examples Analysis

In this paper, the data comes from four different ethylene production plants. They are analyzed and explained in accordance with same technology under different scales and same scales under different technologies.

Energy efficiency evaluation in ethylene production can be considered as an assessment model based on input / output. The research object of energy efficiency evaluation in this paper is ethylene production plants which contains a whole set of production processes. Considered as a whole, production factor of ethylene includes fuel, steam, water and electricity. In order to make the results universal, we analyzed two cases: Same Scale Under Different Technology and Same Technology Under Different Scale [5]. The instance data comes from actual production data every month of each ethylene plants from 2011 to 2013.

4.1 Same Scale Under Different Technology

Based on the four basic DEA model, we evaluate the production efficiency in every month of three years of ethylene plant 1(800,000 tons, Lummus technology) and plant 2(800,000 tons, S&W technology). By using actual production data, we calculate efficiencies for plant 1 and plant 2 under model (1) / (2) / (3) / (4) respectively. And energy consumption makes up the input, while the output is ethylene production. The results are shown in Figure 2 and Figure 3.

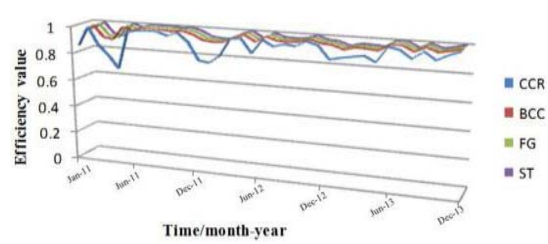

Figure 2: Four DEA models evaluating results of ethylene plant 1

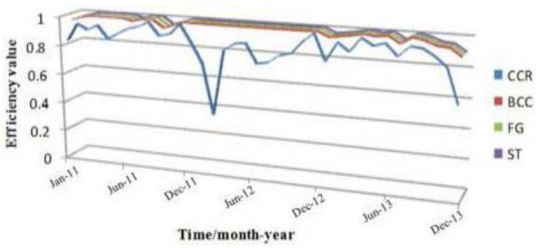

Figure 3: Four DEA models evaluating results of ethylene plant 2

By analyzing and comparing the production energy efficiency of these two ethylene plants in 36 months, the number of decision-making units whose efficiency value is 1 (DEA effective) of CCR model evaluation results are respectively 7 and 3. The proportion of DEA effective in whole units is less than one third [5], which reaches the evaluate discrimination. The number of decision-making units of the two plants whose efficiency value is 1 using BCC, FG and ST models were respectively 13 and 9. Obviously, CCR model has better performance in recognizing the non-effective production month of DEA production plants.

4.2 Same Technology Under Different Scale

Similarly, Based on the four basic DEA model, we evaluate the production efficiency in every month of three years of ethylene plant 3(200,000 tons, Lummus technology) and plant 2(800,000 tons, Lummus technology). The results are shown in Figure 4 and Figure 5.

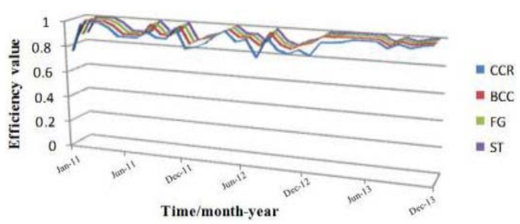

Figure 4: Four DEA models evaluating results of ethylene plant 3

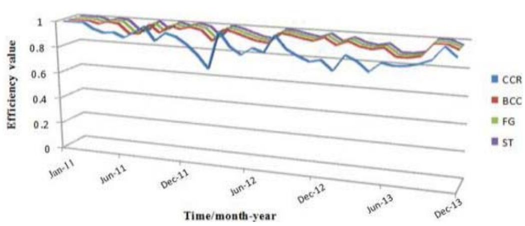

Figure 5: Four DEA models evaluating results of ethylene plant 4

At this time, the number of decision-making units that efficiency value is 1 of CCR model evaluation results are respectively 5 and 6,which are both less than the required one-third. It means that CCR model has great energy efficiency discrimination [5].While the number of other three basic models decision-making units which are DEA effective are respectively were 10 and 11. From the energy efficiency results of two ethylene production unit with same technology under different scale, we can see that CCR model has better discrimination in ethylene production energy efficiency evaluation.

Integrated the result of ethylene production efficiency evaluation using four basic DEA models, we can see that CCR model can evaluate the efficiency of ethylene production better than the others.

4.3 Production Guidance

To further illustrate the superiority of CCR in ethylene production efficiency evaluation compared to the other three DEA basic models, we introduce the CCR relaxation factor results. We can propose guidance to the months that ethylene production efficiency BCC-θ/FG-θ/ST-θ equal to 1 (DEA effective) while CCR-θ is not 1.

The relaxation variable analysis results of the same scale but different technologies ethylene plants shown in table 1, where CCR-θ not equal to 1 but the value of BCC/FG/ST are 1.

Since CCR is a model whose income scale is constant, so relaxation factor s_j^- of the output is not considered, and the experimental results are all 0. The table shows the result of the relaxation factor s_j^+ which is imported by ethylene production system. The four inputs are fuel total investment, the total investment of steam, water and electricity investments, respectively. The corresponding value represents the reduction of the input of the non-effective month to improve the ethylene production efficiency. Take the result of May in 2011 for example, ethylene production efficiency value of the month reached 1 (DEA effective) when water input reduced 0.3GJ/t ethylene and electrical input reduced 0.11GJ/t ethylene. In this way, we can improve productivity and save energy. Other months in which ethylene production plants are non-effective can make the same improvement by referring to corresponding relaxation factor, so as to achieve effective energy efficiency. The results are shown in Figure 6 and Figure7:

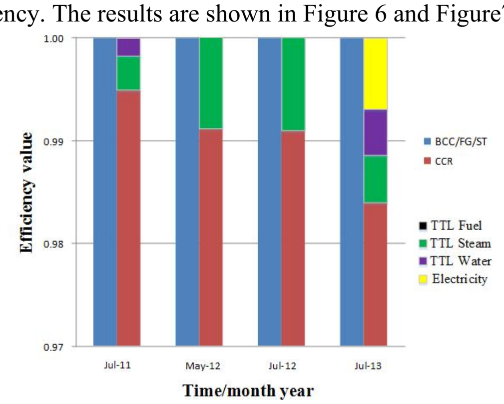

Figure 6: Production guidance of ethylene plant 1

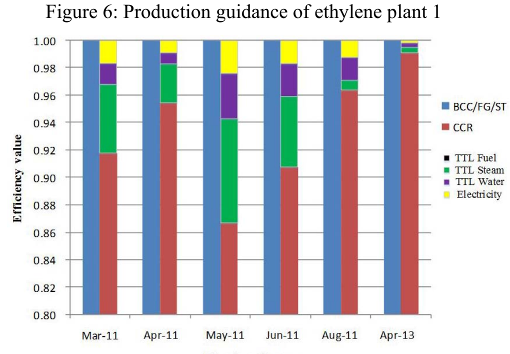

Figure 7: Production guidance of ethylene plant 2

Table 1: Production CCR relaxation factors of ethylene plant 1 and 2 (GJ/t ethylene)

	Plant1					Plant2					
	May-11	Jul-11	May-12	Jul-12	Jul-13	Mar-11	Apr-11	May-11	Jun-11	Aug-11	Apr-13
Fueltoal	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Steamtoal	0.00	0.15	0.49	0.06	0.01	1.53	1.26	1.66	1.05	0.27	0.34
Watertoal	0.30	0.00	0.00	0.00	0.01	0.44	0.26	0.56	0.38	0.44	0.37
Electricity	0.11	0.00	0.00	0.00	0.03	0.44	0.20	0.31	0.13	0.31	0.16

Table 2: Production CCR relaxation factors of ethylene plant 3 and 4 (GJ/t ethylene)

	Plant3					Plant4				
	Feb-11	Sep-11	Dec-11	Apr-13	May-13	May-11	Nov-11	Jan-12	Oct-13	Nov-13
Fueltoal	0.00	7.50	0.97	0.00	0.00	0.46	0.00	1.14	0.00	0.00
Steamtoal	0.93	2.10	0.00	0.00	0.00	0.00	0.00	0.11	0.53	0.37
Watertoal	0.12	1.50	0.16	0.00	0.17	0.36	0.00	0.12	0.33	0.22
Electricity	0.00	0.00	0.00	0.07	0.06	0.00	0.01	0.00	0.04	0.02

The figures show that the discrimination of BCC, FG and ST models is lower than the CCR model in evaluation system of ethylene production. CCR model can detect more months whose production is non-effective. Adjusting energy production according to the relaxation factor is helpful to improve productivity of the month. At the same time, we can make production guidance to achieve the purpose of energy saving.

Similarly, the relaxation variable analysis results of ethylene plants under the same technology but different scales are shown in table 2, which CCR-θ is not equal to 1 but the value of BCC/FG/ST are 1.

The results in the tables can be made to guide the production of non-effective month of ethylene plant 3 and 4. For example, in September 2011, material input should be reduced by 0.93GJ/t ethylene, steam input should be reduced by 0.12GJ/t ethylene and water input should be reduced by 1.5 GJ/t. Thus, the ethylene production efficiency of the month can be DEA effective. The production guidance of non-effective months of other plants is shown in Figures 8 and 9:

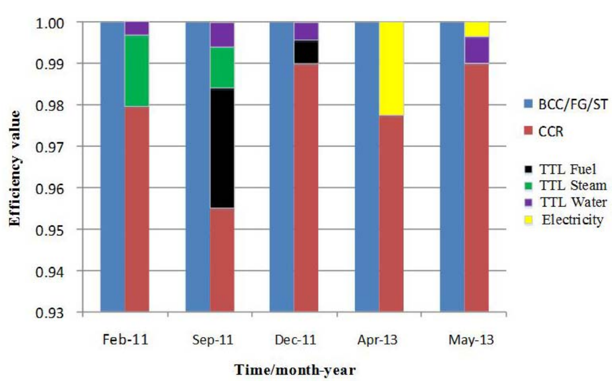

Figure 8: Production guidance of ethylene plant 3

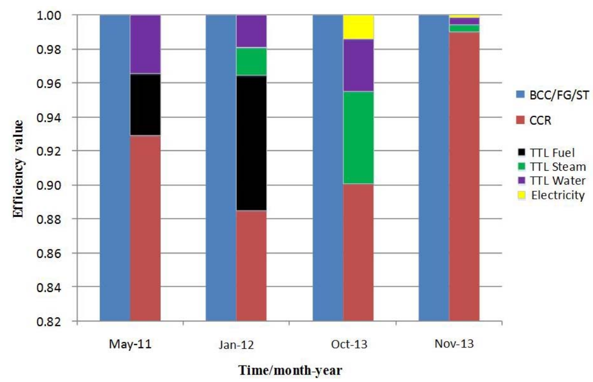

Figure 9: Production guidance of ethylene plant 4

In figures 6, 7, 8 and 9, the blue bars in each chart represent the efficiency value of BCC/FG/ST equaling to 1, and the same month of CCR is not 1 which is shown in dark red bars. Furthermore, the CCR bars are stacked with fuel/water/steam/electricity bars, which aim to convey the production guidance clearly. The size of stacked bars means the input adjustment of non-effective month.

In short, compared to BCC, FG and ST models, CCR model can guide ethylene production more effectively, which can improve production efficiency and save energy.

5 Conclusions

This paper analyzes the principles of four basic DEA models and makes energy efficiency evaluation and production guidance of production situations of ethylene plants under different technologies and scales. By the energy efficiency evaluation of ethylene production using the relative efficiency of decision-making units, we obtain that CCR model has better discrimination than the other three basic models. The CCR can distinguish more decision-making units whose productivity is not 1. Meanwhile, CCR model can better analyze and evaluate ethylene production efficiency. Meanwhile, by importing relaxation factor in the CCR model, we could guide and improve production situations of the ineffective production months to enhance production efficiency of ethylene as well as reach the target of energy saving and reducing consumption.

By analyzing and comparing four DEA basic models, it can be more objective and comprehensive to analyze and select DEA model which is more suitable for production evaluation of ethylene industry. By verifying and analyzing actual production of ethylene plants from different angles, we confirmed the effectiveness and the universality of DEA-CCR model and provided theoretical basis for choosing suitable energy efficiency evaluation method of ethylene production. Moreover, in the field of energy efficiency evaluation in ethylene process, there is further space for CCR model research, e.g. improving the DEA-CCR evaluation model to improve the accuracy and discrimination of energy efficiency estimation in ethylene process. Furthermore, we can add in carbon emissions thought, i.e. carrying out research in efficiency evaluation of ethylene process from the perspective of energy conservation and carbon emissions reduction, which contributes to making better guidance in ethylene plant energy saving and improving ethylene productivity.

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