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Performance Analysis of China Ethylene Plants by Measuring Malmquist Production Efficiency Based on an Improved Data Envelopment Analysis Cross-Model

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Supporting Information

ABSTRACT: Data envelopment analysis (DEA) has been widely used for efficiency evaluation of industrial plants. A conventional DEA model may easily lead to the situation where more than one-third of efficiency values are set to 1, so it is hard to analyze the pros and cons of the multi-decision-making units. The DEA cross-model can distinguish the pros and cons of the effective decision-making units, but it is unable to indicate the improvement direction of the ineffective decision-making units. This paper proposes an efficiency analysis method based on an improved DEA cross-model, which can get higher efficiency discrimination in identifying the efficiency state of the decision-making units compared with the conventional DEA model. The improved DEA cross-model avoids the impacts of unreasonable weight allocation of input and output indices. Meanwhile, self-evaluation of the improved DEA cross-model with the slack variables can find the improvement direction of the ineffective decision-making units. Also, the Malmquist productivity index (MPI) based on the improved DEA cross-model can comprehensively consider various input−output factors and obtain dynamic consistent analysis performance of industrial plants. To get relative effectiveness of ethylene plants under different technologies and different scales, the performance analysis of 19 ethylene plants in China were executed by proposed MPI. According to the results, various indices of MPI are evaluated over time by the improved DEA cross-model to obtain the root causes and direction of performance improvement of ethylene plants. As a result, the method proposed in this paper is effective and practical.

1. INTRODUCTION

The ethylene industry is one of the most important parts of the petrochemical industry. The production of the ethylene complex has become a main sign of industrialization of a country. In 2008, the ethylene production capacity of China Petrochemical Corporation was 9475 kt/a, and the fuel plus power consumption (standard oil) was 649.36 kg per ton of ethylene produced.[1] Meanwhile, China National Petroleum Corporation's ethylene production was 2676 kt/a, and the average fuel plus power consumption (standard oil) was 714 kg per ton of ethylene produced in 2008.[2] The statistics have shown that the energy efficiency of ethylene production in China is significantly lower than that of the developed countries, thus there is considerable space for improving the energy efficiency of ethylene production in China. Moreover, energy consumption of ethylene plant costs account for over 50% of operating costs,[3], therefore the study of the performance efficiency evaluation of ethylene plants will achieve great economic benefits.

Enterprises often use the mean method and the optimal index method to establish the benchmark performance analysis,[4] but the two methods do not take into consideration energy saving knowledge, so they cannot give a performance efficiency value benchmarking of optimal factors and indices to guide the analysis of the actual performance efficiency state. Moreover, although efficiency analysis of ethylene plants based on the data fusion method has obtained good results, it does not consider the role of influential factors on energy consumption indicators.[5,6] The method based on the analytic hierarchy process (AHP) and data envelopment analysis (DEA) model has been widely applied to the efficiency evaluation of agriculture, logistics, and other industries.[7,8] However, in ethylene performance they do not succeed, as crude oil was not taken into consideration.[9,10] Therefore, this paper studies the performance analysis of China ethylene plants based on the DEA-integrated Malmquist production index (MPI).

In 1978, the famous operational research experts A. Charnes, W. W. Cooper, and E. Rhodes first proposed the DEA method. They used this method to make a "production apartment", which had multiple inputs and multiple outputs. The results are defined especially into "sizable effective" and "technological effective" results. Wade and Larry provided a brief sketch of some of the important areas of research in DEA that have emerged over the past three decades.[11] The application of DEA turned out to be very satisfactory and effective,[12] especially in the petrochemical industry. And the collinearity of input−output indicators (highly relevant) did not affect the stability and reliability of the model.[13] Sueyashi et al. evaluated the operational, environmental, and both-unified performance of coal-fired power plants based on the DEA approach and DEA window analysis for environmental assessment in a dynamic time shift, respectively.[14,15] Yang et al. used six DEA-based performance evaluation models to

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investigate the performance of Chinese coal-fired power plants.[16] To detect the important criteria affecting the efficiency levels and find the common characteristics of the most inefficient firms, Erturk and Turut-Asik analyzed the performance of 38 Turkish natural gas distribution companies by using a non-parametric method, DEA.[17] Sueyoshi and Goto incorporated an output separation (desirable and undesirable outputs) for the performance evaluation of Japanese fossil fuel power generation.[18] Liu et al. evaluated the power-generation efficiency of major thermal power plants in Taiwan during 2004−2006 using the DEA approach.[19] Riccardi et al. analyzed the efficiency of the world cement industry in the presence of undesirable output by combining the application of DEA and directional distance function.[20] However, the quantities of input and output indicators and the number of samples had a profound impact on the results of DEA analysis.[21,22] The conventional DEA model can lead to the situation where more than one-third of efficiency values are set to 1,[23,24] so it means efficiency discrimination is poor. It also cannot acquire effective decision-making units. Thus, the conventional DEA model can only distinguish the effective and ineffective units when analyzing enterprise production plant efficiency, but cannot give further evaluation and comparison of multieffective decision-making units. Moreover, to get the maximum efficiency evaluation index of each decision-making unit, the weight allocation of input and output indicators are usually unreasonable.[12] Therefore, the DEA cross-evaluation model (DEA cross-model) is proposed to analyze the performance efficiency index of the petrochemical industry.

In 1986, Sexton proposed the DEA cross-evaluation method.[25] Wang et al. introduced several kinds of DEA cross-model and its application.[26] Chen compared technical efficiency and cross-efficiency scores in the electricity distribution sector in Taiwan through a DEA framework.[27] Lu et al. provided a theoretical basis for reference in grasping the actual level of thermal power units and charting the direction of improvement by DEA Cross-evaluation model.[28] Yu et al. identified the most efficient scenario and estimated the efficiency of each information-sharing scenario in supply chains by a cross-efficiency DEA approach.[29] However, the previous DEA Cross-evaluation model did not put forward the improvement direction of ineffective decision-making units in the self-evaluation. This paper proposes an improved DEA cross-model with the slack variables which can make up for the conventional DEA cross-model. The self-evaluation of the improved DEA cross-model with the slack variables can figure out the improvement direction of ineffective enterprise more accurately. Meanwhile, the cross-evaluation of the improved DEA cross-model can distinguish the pros and cons of the effective decision-making units.

This improved DEA cross-evaluation model can only analyze statically and identify the difference of the efficiency of the decision making units (DMUs) on the physical quantities, and it cannot determine the real cause of the difference in the DMUs' efficiency. Therefore, to make clear the direction of improving performance and key indices, the MPI is applied to analyze the efficiency of DMUs over time and identify the real reason for the difference of DMUs' efficiency.

In 1953, Swedish economist Sten Malmquist first proposed the Malmquist index. At the same time, Shephard proposed the corresponding distance function in the production analysis. In 1982, Cave proposed the MPI and constructed it with the ratio of distance function. Distance function has advantages in multi-input and output technology, and it has been proved as a very important measure of production pattern. In 1978, Charnes, Cooper and Rhodes proposed the DEA method which measured technical efficiency by linear programming, thus the concept of distance function (technical efficiency) was widely accepted and the DEA become an important method in production analysis. Based on DEA method, in 1994 Fare et al. transformed the MPI from theory into practice, and decomposed MPI into the change of technical efficiency, technical progress, and scale efficiency, so that production efficiency could be analyzed with further refinement.[30] In recent years, MPI has become one of the most widely used approaches in the analysis of productivity. Xue et al. measured the productivity of the construction industry in China by using DEA-based MPIs.[31] Wang and Lan studied a new approach to measure MPI by using both optimistic and pessimistic data envelopment analyses (DEA) simultaneously.[32] Mehmet studied the productivity changes of forest enterprises in Turkey by the nonparametric Malmquist approach.[33] Egilmez and McAvoy assessed the relative efficiency and productivity of U.S. states in decreasing the number of road fatalities by the DEA-based Malmquist index model.[34] Kao studied a common-weights DEA model for time-series evaluations to calculate the global MPI so that the productivity changes of all DMUs had a common basis for comparison.[35]

Considering the shortages of conventional DEA model and DEA cross-model, this paper proposes an improved DEA cross-model with the slack variables to analyze the statical efficiency of ethylene plants. Then the MPIs are calculated by the improved DEA cross-model to analyze the dynamic efficiency of the ethylene industry and identify the real reason for the difference of DMUs' efficiency, which can be a more accurate evaluation of the technical efficiency change, the technological change, pure technical efficiency change, scale efficiency change, and the total factor productivity change of MPI over time. This approach is used to evaluate and analyze the performance of petroleum chemical equipment in the ethylene industry. It is reasonable to figure out efficiency indices of each plant and provide some advice about operation guidance for energy saving and performance improvement.

2. INPUTS AND OUTPUTS ANALYSIS OF CHINA ETHYLENE PLANTS

In the DEA model, the number of inputs and outputs lowers the discrimination of analysis results. Moreover, the lower is the correlation between inputs or outputs, the greater is the impact that the number of input−output has on discrimination. In the case for which that efficiency distinction is not high (such as result of ref 36) enough, the judgments of the overall efficiency and the efficiency frontier are not reliable. Especially for the efficiency frontier, because there is the default effective problem, a comprehensive judgment by a combination of superefficiency value, the reference number, the total weight, and so on is required. The number of input−output factors has a significant influence on the analysis results of the DEA model. For the same sample, an increasing number of the input−output factors can make the effective units proportion and the average efficiency increase. For the same input−output factors, when the sample size is small, the decreasing number of samples can also make the effective units proportion and the average efficiency increase. In the DEA model, selection of the appropriate input−output factors will lead to a correct conclusion.

The DEA model requires a relatively small number of samples.[23] In general, the rules of relationship between the number of samples and the number of factors follow the principle that the number of samples (referred to as the number of

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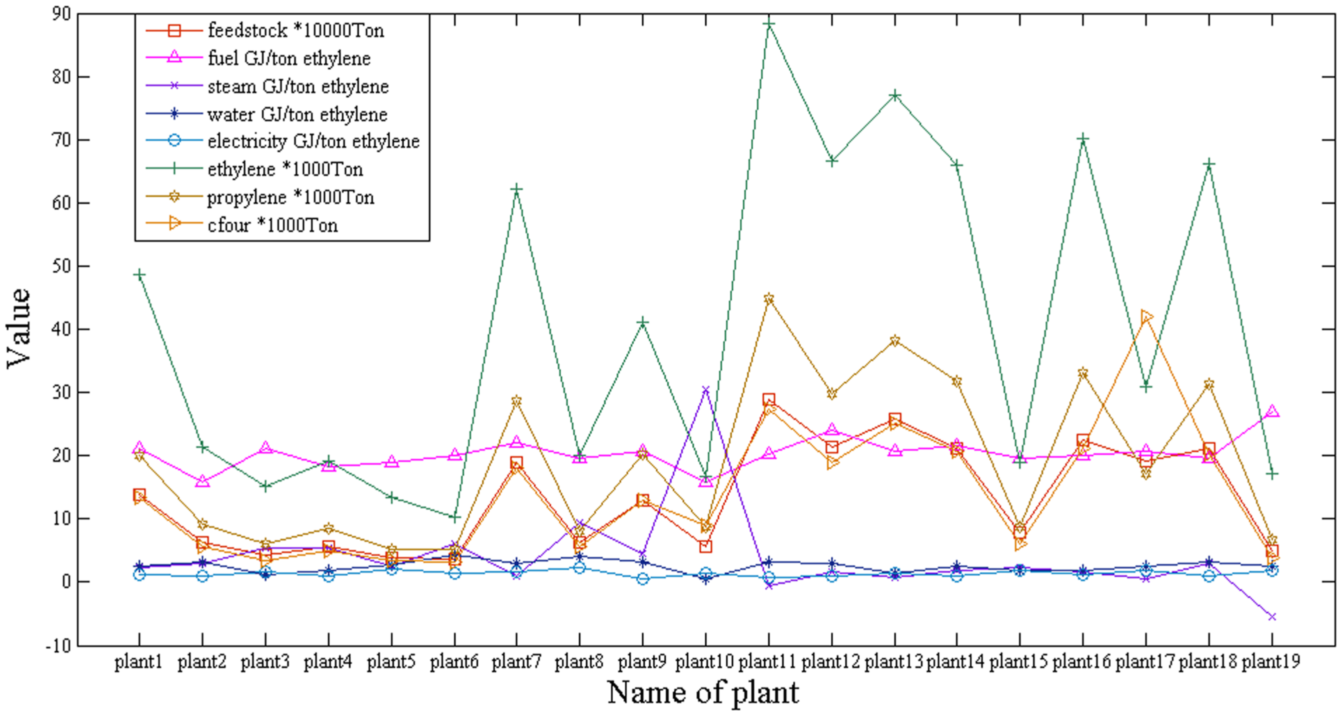

Figure 1. Main input−output data of various ethylene production plants in 2009.

decision-making units) should not be less than the number of inputs multiplied by the number of outputs or three times the sum of inputs and outputs, and the number of inputs and outputs can be up to 10. The principle is determined by data simulation results and the minimum requirements for efficiency discrimination.[21,22,24]

To investigate production efficiency of ethylene plants, it is necessary to identify major inputs and outputs. For ethylene plants, the production efficiency is directly related to the main factors: (1) feedstock; (2) utilities; (3) products. The following work is to construct an input−output model for the improved DEA cross-model and the calculation of MPI of ethylene plants.

There are seven classes of process technologies in Chinese ethylene product industries.[37] The main energy types are included in the ethylene utilization boundary as follows: the water including recycle water, industrial water, and boiler water; the power (electricity); steam including superhigh pressure steam, high pressure steam, middle and low pressure steam; fuels including fuel gas, light oil, and heavy oil; N2 and compressing air. Because of the lowest consumption of N2 and compressing air among energy types, they were not computed considering the energy efficiencies of the ethylene product process. According to the statistics, the energy consumption fees are up to more than 50% of the total cost for the ethylene product process. Therefore, the consumption of feedstock and utilities mainly including fuel, steam, water, and electricity are taken as inputs of ethylene production, and the yields of the main products, ethylene, propylene, and C_4, are taken as outputs.[9,10,37,38] To make sure that the values among variables are comparable, it is necessary to convert physical units of fuel, steam, water, and electricity into GJ uniformly, according to the conversion relations of Table 3.0.2 and Table 3.0.3 in the "Petrochemical Design Energy Consumption Calculation Method" (SH/T3110−2001).[39] The main raw material of ethylene, naphtha, hydrogenated tail oil, light diesel oil, raffinate oil, and C_3, C_4, C_5, et al., are summed as feedstock for processing. The monthly production data of 19 ethylene production plants nationwide from 2001 to 2010 are selected for the analysis, because the monthly data are time-series data and the sample granularity of each variable can comply with the industrial statistical requirement.

Therefore, to represent the yields of products in one year, the average yields of products for each plant can be obtained by averaging the sum yields of 12 months for every product. Figure 1 and Figure 2 show input−output data of all 19 ethylene plants in 2009 and 2010, respectively.

3. THE STATIC EFFICIENCY ANALYSIS OF CHINA ETHYLENE PLANTS BASED ON IMPROVED DEA CROSS-MODEL

DEA cross-evaluation is a new method that takes DEA as a sorting tool of multicriteria decision making. This method avoids the unreasonable weight allocation of input and output by conventional DEA, so that each DMU can be evaluated effectively.[13]

3.1. Improved DEA Cross-Model. Assume that there are n units or plants, each DMU has m inputs and s outputs, where $x_i = (x_{1i}, x_{2i}, ..., x_{mi})^T > 0$, $y_i = (y_{1i}, y_{2i}, ..., y_{si})^T > 0$, x_{ij} and y_{ri} denote the jth input and the rth output of DMU$_i$ ($i = 1,2,...,n$; $j = 1,2,...,m$; $r = 1,2,...,s$.), respectively. DMU$_i$ is evaluated by the following CCR(Charnes, Cooper and Rhodes) model of DEA.

$$\begin{cases} \max \dfrac{y_i^T u}{x_i^T v} = E_{ii} \\ \dfrac{y_l^T u}{x_l^T v} \le 1 \quad l = 1, 2, \cdots, n \\ u \ge 0, \ v \ge 0, \ u \ne 0, \ v \ne 0 \end{cases} \tag{1}$$

In which $v = (v_1, v_2, ..., v_m)^T$ and $u = (u_1, u_2, ..., u_s)^T$ denote weight coefficients of the m inputs and s outputs, respectively. The CCR

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model can be transformed into equivalent linear programming (LP) ones by the Charnes−Cooper Transform.

$$\begin{cases} \max y_i^{\mathrm{T}} u = E_{ii}, \\ y_l^{\mathrm{T}} u - x_l^{\mathrm{T}} v \le 0, \quad l = 1, 2, \cdots, n, \\ x_i^{\mathrm{T}} v = 1, \\ u \ge 0, \quad v \ge 0 \end{cases} \tag{2}$$

Assume that equations 2 have the optimal solution u_i^* and v_i^* called the optimal weight and denoted $w_i^* = (v_i^*, u_i^*)^{\mathrm{T}}$, and the optimal value is $E_{ii} = y_i^{\mathrm{T}} \mu_i^*$ denoting the efficiency of DMU$_j$, that is, a self-evaluation value.[13] In DEA, if $E_{ii} = 1$, then DMU$_i$ is considered effective, and if $E_{ii} < 1$, then DMU$_i$ is considered ineffective.

By using the self-evaluation value E_{ii} of DMU$_i$ in eq 2, $i \in \{1,2,...,n\}$ and $k \in \{1,2,...,n\}$ are given to solve the following LP:[40,41]

$$\begin{cases} \min y_k^{\mathrm{T}} u \\ y_l^{\mathrm{T}} u - x_l^{\mathrm{T}} v \le 0, \quad l = 1, 2, \cdots, n, \\ y_i^{\mathrm{T}} u = E_{ii} x_i^{\mathrm{T}} v, \quad x_k^{\mathrm{T}} v = 1, \\ u \ge 0, \quad v \ge 0 \end{cases} \tag{3}$$

Then the cross-evaluation value can be calculated by the optimal solution u_{ik}^* and v_{ik}^* of eq 3:

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

Finally, the cross-evaluation values constitute a cross-evaluation matrix:

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

In which main diagonal element E_{ii} and nondiagonal element E_{ik} $(k \ne i)$ denote the self-evaluation value and cross-evaluation value, respectively. The ith row of $\mathbf{E}$ denotes the evaluation values of each decision making unit for DMUi. The higher these values are, the better is the DMU$_i$. Thus, the mean value of the ith row of $\mathbf{E}$

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

is used as a criterion to measure DMU$_i$. e_i can be seen as the total evaluation of each decision making unit for DMU$_i$. The higher is e_i, the better is DMU$_i$.

The self-evaluation model (CCR model) in the DEA cross-model mentioned above, however, fails to point out the improvement direction for the noneffective decision-making units. To facilitate better checkout of the improvement direction for the effectiveness and ineffectiveness of DEA, we use the equation form of the dual model of eq 2 (with slack variables and non-Archimedean infinitesimal ε), that is, the input-oriented DEA model:

$$\begin{cases} \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji} + s^- = \theta x_{ji}, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri} - s^+ = y_{ri}, \quad r = 1, 2, ..., s \\ \lambda_i \ge 0, \quad i = 1, 2, ..., n, \\ s^- \ge 0, \quad s^+ \ge 0 \end{cases} \tag{7}$$

Where e is a non-Archimedean value designed to enforce strict positivity on the variables. ε is an "abstract number", which is less than any positive number and greater than 0. Specific value of ε is set as small as possible to ensure ε closing to the infinitesimal. Also, in order to ensure the convergence of computing, the specific value of ε is set as large as possible. In this paper, to separate efficient and weakly efficient DMUs, we set $\varepsilon = 10^{-6}$.[42−45] s_t^- and s_t^+ are introduced as slack variables. $s_t^- = (s_t^{1-}, s_t^{2-}, ..., s_t^{m-})^{\mathrm{T}}$, $s_t^+ = (s_t^{1+}, s_t^{2+}, s_t^{r+})^{\mathrm{T}}$ denote the redundant amount of m input items and the insufficient amount of s output items, respectively. $e_1^{\mathrm{T}} = (1,1,...,1) \in R^m$, $e_2^T = (1,1,...,1)^T \in R^s$, θ denotes the valid value for the decision-making unit, i.e., the effective utilization degree of inputs relative to output.

By using eq 7, not only the self-evaluation value θ of DMU$_i$, that is, E_{ii} $(1 \le i \le n)$, but also the input redundant amount s_t^- and the output insufficient amount s_t^+ of ineffective decision-making units can be calculated. By substituting the calculated decision-making self-evaluation model of eq 7 into eq 3, we can obtain the cross-evaluation model of decision-making units by eq 4, eq 5, and eq 6. Furthermore, the input redundant amount and output insufficient amount can guide and improve the input−output amount of ineffective decision-making units.

The flowchart of conventional and improved DEA cross-model for efficiency analysis is shown in Figure 3.

3.2. The Static Efficiency Analysis of China Ethylene Plants. The main inputs (the consumptions of feedstock, steam, fuel, water, and electricity) of ethylene plants are taken as the inputs of the improved DEA cross-model, and the main outputs (the yields of ethylene, propylene, and C_4) of ethylene plants are taken as outputs of the improved DEA cross-model. As shown in Figure 4, the DEA efficiency values of various plants in 2008, 2009, and 2010 can be obtained by the self-evaluation CCR model eq 2 in the first step of the conventional DEA cross-model.

The DEA efficiency values are the same by eq 2 and eq 7. The difference is that the self-evaluation efficiency values and slack variables s^- and s^+ of various plants can be obtained by self-evaluation eq 7. Table 1 and Supporting Information Table A.1 are filled with self-evaluation efficiency values, the input redundant amount s^- (s^{1-}, s^{2-}, s^{3-}, s^{4-}, s^{5-} are the redundant amount of feedstock, fuel, steam, water, and electricity, respectively), and the output insufficient amount s^+ (s^{1+}, s^{2+}, s^{3+} are the insufficient amount of the yields of ethylene, propylene, and carbon 4, respectively) of all plants throughout the ethylene industry in 2009 and 2010, respectively.

Table 1 shows that, self-evaluation efficiency values of some plants are 1, such as plant 1, plant 3, plant 4, and plant 9, et al., which indicate that the self-evaluations of these plants are effective. But for the plants which self-evaluation efficiency values are less than 1, the improvement direction of various plants can be obtained by input slack variables. For example, the

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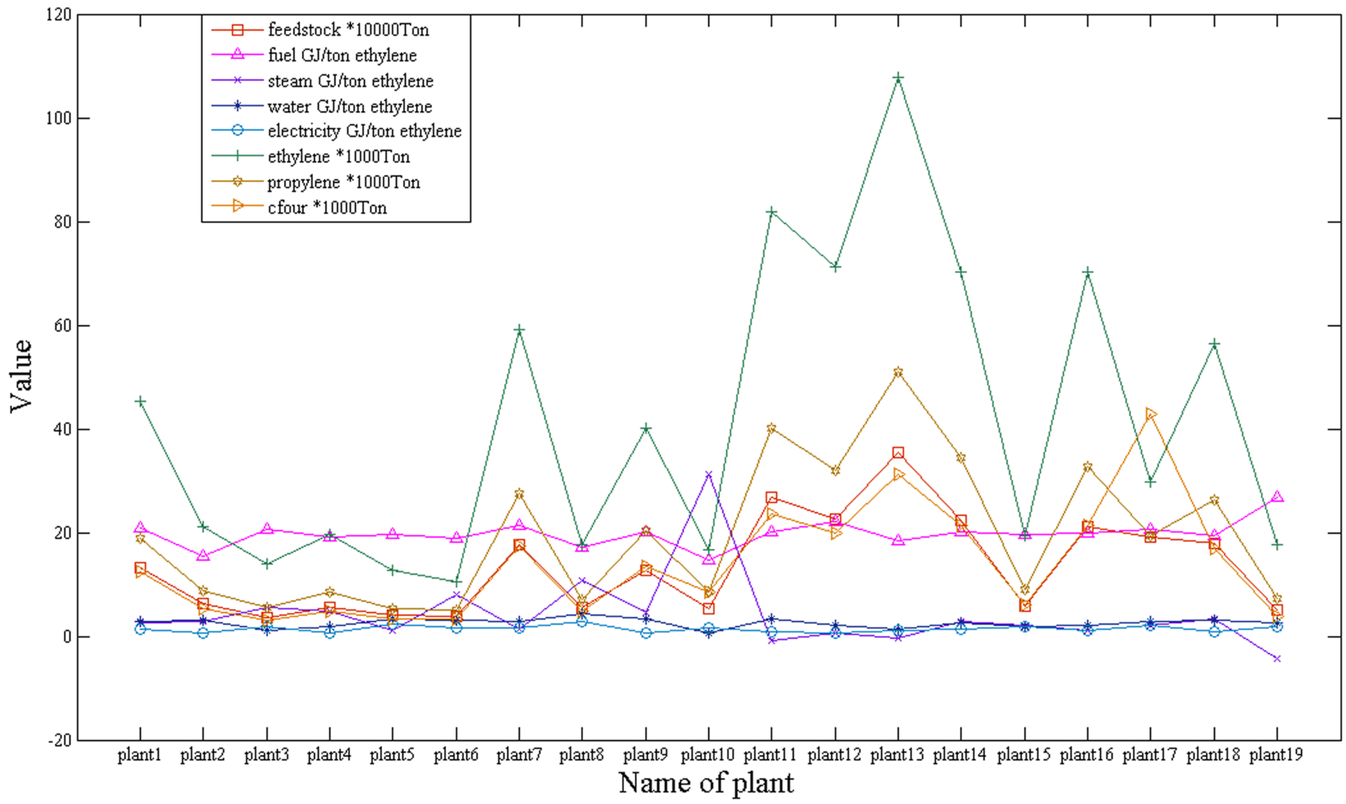

Figure 2. Main input−output data of various ethylene production plants in 2010.

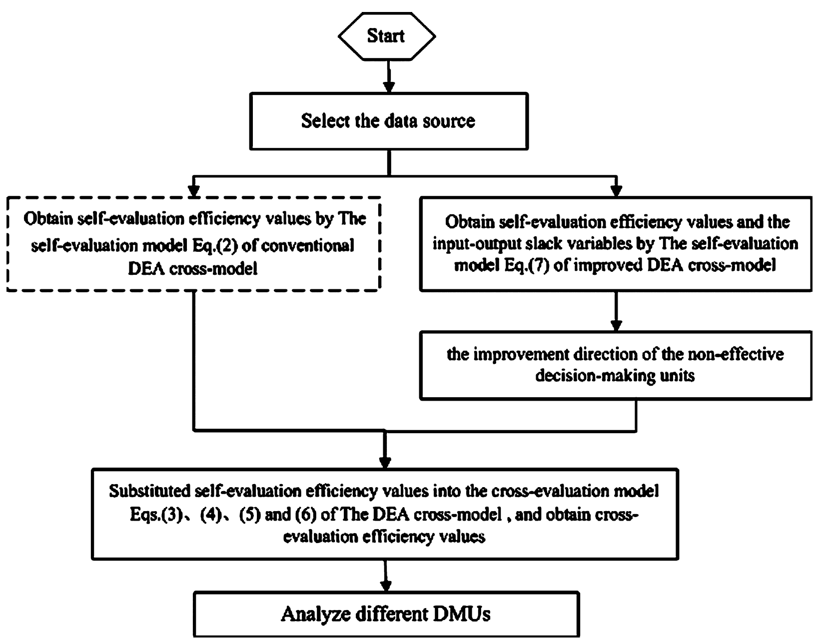

Figure 3. Flowchart of conventional and improved DEA cross-evaluation model for efficiency analysis of enterprise.

self-evaluation efficiency value of plant 2 is 0.9901. If its ethylene production inputs reduce 1.9434 GJ of steam, 1.6409 GJ of water, and 0.1311 GJ of electricity per ton of ethylene, and outputs increase 24.9511 ton of C_4, then the DEA efficiency value of the ethylene plant can achieve the effective level. The other non-effective ethylene production plants can also undergo a similar analysis. Because eq 7 requires a comprehensive judgment by a combination of superefficiency values, the number of input−output factors has a significant influence on the analysis results of the DEA model. Meanwhile, the scales of plants 11, 12, and 13 are about one million tons and larger than the others, so these efficiency values are higher than 1, and the production of these plants is in good condition.

A similar conclusion can be drawn from Supporting Information Table A.1. For example, the self-evaluation efficiency value of plant 8 is 0.8764. If its ethylene production inputs reduce by6.0523 GJ of fuel, 2.7594 GJ of water, and 1.1645 of GJ electricity per ton of ethylene, and outputs increase to

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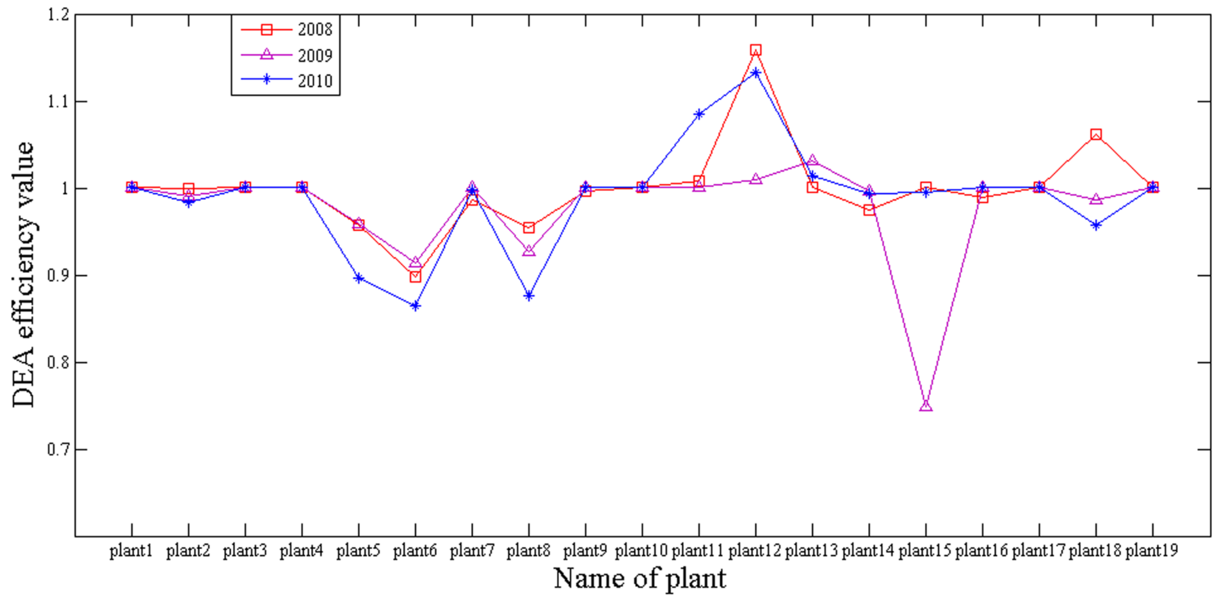

Figure 4. Self-evaluation efficiency values of various plants in 2008, 2009, and 2010.

Table 1. Self-Evaluation Efficiency Values of Various Plants in 2009[a]

plant	s^{1-}	s^{2-}	s^{3-}	s^{4-}	s^{5-}	s^{1+}	s^{2+}	s^{3+}	θ
plant 1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 2	0.0000	1.9434	0.0000	1.6409	0.1311	0.0000	0.0000	24.9511	0.9901
plant 3	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 4	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 5	0.0000	7.5111	0.3390	1.8308	1.2414	0.0000	221.5636	0.0000	0.9592
plant 6	0.0000	11.6366	0.0000	3.3024	1.0308	0.0000	0.0000	531.9042	0.9138
plant 7	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 8	0.0000	9.2047	7.0290	2.7642	1.5530	0.0000	399.3701	0.0000	0.9268
plant 9	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 11	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 12	6076.6243	3.0304	0.2186	0.0000	0.0000	0.0313	2084.0183	1191.0588	1.0087
plant 13	8382.5297	0.6384	0.0000	0.0000	0.0518	0.0000	0.0000	0.0000	1.0316
plant 14	0.0000	2.5710	0.6875	0.0000	0.0000	0.0000	0.0000	0.0000	0.9963
plant 15	0.0000	7.3633	0.0000	0.4493	0.8560	0.0000	0.0000	0.0000	0.7479
plant 16	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 17	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000
plant 18	0.0000	0.0000	2.3382	0.3218	0.0000	0.0000	520.1019	0.0000	0.9867
plant 19	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000

[a]Note: the unit of s^{1-}, s^{1+}, s^{2+}, s^{3+} is Ton, and the unit of s^{2-}, s^{3-}, s^{4-}, s^{5-} is GJ/ton ethylene. θ denotes the efficiency value for the ethylene plant.

612.2247 ton of propylene, then the self-evaluation efficiency value of the plant can be effective. However, in Table 1 and Supporting Information Table A.1, the self-evaluation efficiency analysis for the ethylene production plants in 2009 and 2010 show that too many self-evaluation efficiency values of plants are 1 so that these DEA efficiency values of effective ethylene production plants cannot be analyzed.

Generally, the conclusion will not be obtained if the number of the effective decision-making units exceeds 1/3 of the total by DEA.[20] In fact, the self-evaluation efficiency values of 11 plants (such as plant 1, 3, 4, 9, 10, etc.) are 1 for 2008, 2009, and 2010 in Figure 4, for which the proportion has far exceeded 1/3. So, it is necessary to introduce the DEA cross-model for analysis.

The efficiency values of various plants for 2008, 2009, and 2010, which are calculated by conventional DEA cross-model eqs 2–6, are shown in Figure 5. It is obvious that the improvement direction of the ineffective decision-making units cannot be obtained. Therefore, the second step solution of the improved DEA cross-model that is proposed in the paper can get the efficiency values E_{ii} of various plants in 2008, 2009, and 2010 by eqs 3–7, as shown in Figure 6.

The results of the conventional DEA cross-model in Figure 5 are basically consistent with the results of the improved DEA cross-model in Figure 6, which indicates the correctness of the proposed improved DEA cross-model. However, the self-evaluation model of the conventional DEA cross-model cannot obtain the improvement direction of noneffective decision-making units, while the improved DEA cross-model can easily distinguish the DEA efficiency level of various plants and the self-evaluation model can obtain the improvement direction of ineffective decision-making units.

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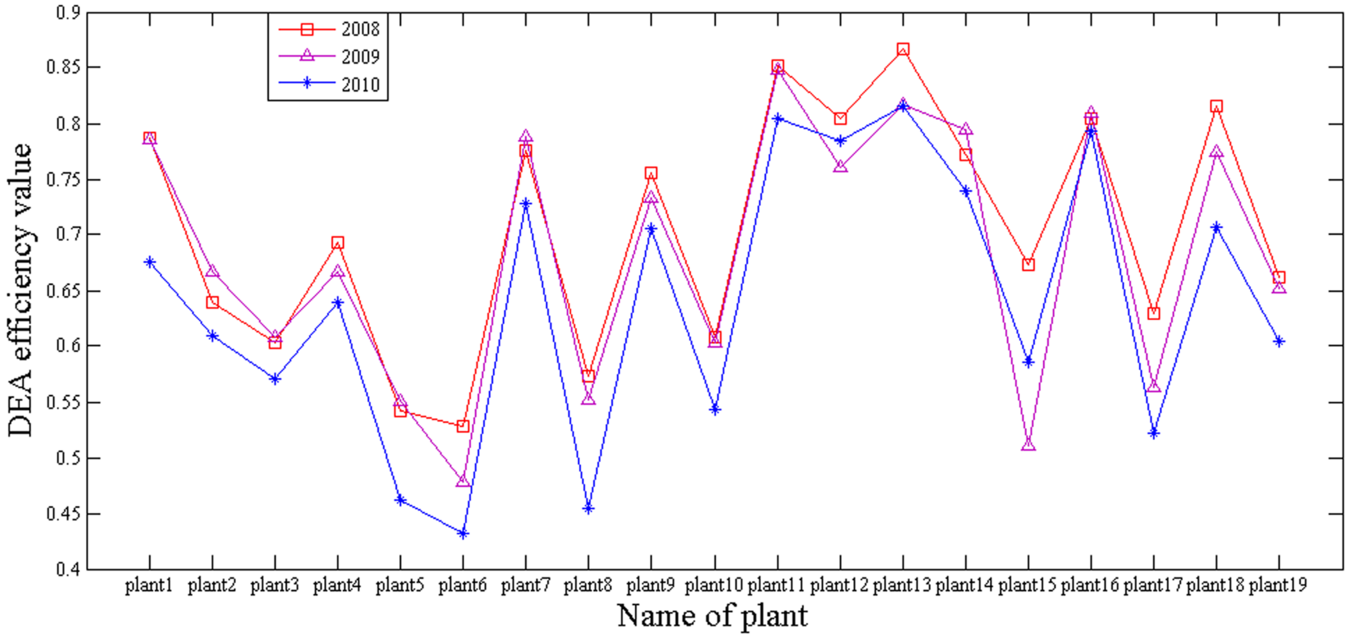

Figure 5. Conventional DEA cross-model efficiency values of all plants in 2008, 2009, and 2010.

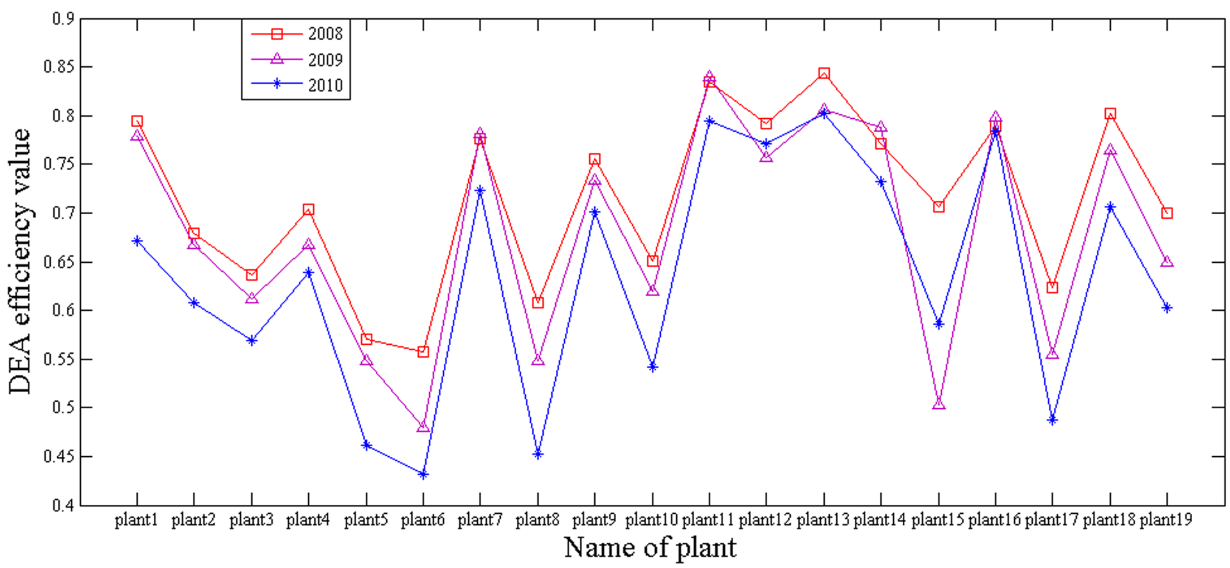

Figure 6. Improved DEA cross-model efficiency values of all plants in 2008, 2009, and 2010.

Figure 6 shows that, in 2008, the DEA efficiency value of plant 13 is the highest and plant 6 is the lowest. In 2009, the DEA efficiency value of plant 11 is the highest and plant 6 is the lowest. In 2010, the DEA efficiency value of plant 13 is the highest and plant 6 is the lowest. From 2008 to 2010, the DEA efficiency value of plant 12 declines from 2008 to 2009, but rises again in 2010. And for multiple plants, such as plant 1, plant 4, and plant 9, etc., ethylene DEA efficiency values declined slightly. As an example, the monthly DEA efficiency values of plant 1 from 2001 to 2010 are shown in Figure 7, which is obtained by the improved DEA cross-model.

It is shown from Figure 7 that the DEA efficiency value of plant 1 is lowest in about July every year, because in this month every year plant 1 needs to reduce ethylene production and maintain equipment. Before 2006 ethylene DEA efficiency was generally low, but after 2006, ethylene DEA efficiency became higher, even in July in 2007, which has the minimum DEA efficiency, because in this month plant 1 cut off overhaul. Comparing with other plants and their own historical data, we can do a static analysis of the DEA efficiency of each plant on the basis of physical quantities. Therefore, to make clear the direction of improving performance and key indices in the technical improvement and the scale of production increase, we adopt the MPI to identify the real reason for the difference of DMUs' efficiency over time.

4. PERFORMANCE ANALYSIS OF CHINA ETHYLENE PLANTS OVER TIME BY MEASURING MALMQUIST PRODUCTION EFFICIENCY

The improved DEA cross-model can distinguish the production efficiency indices of different plants and obtain the production improvement direction of ineffective plants on the physical quantities by self-evaluation. However, the improved DEA cross-model only analyzes static efficiency of ethylene plants per year, and the obtained Malmquist Index of various plants can give

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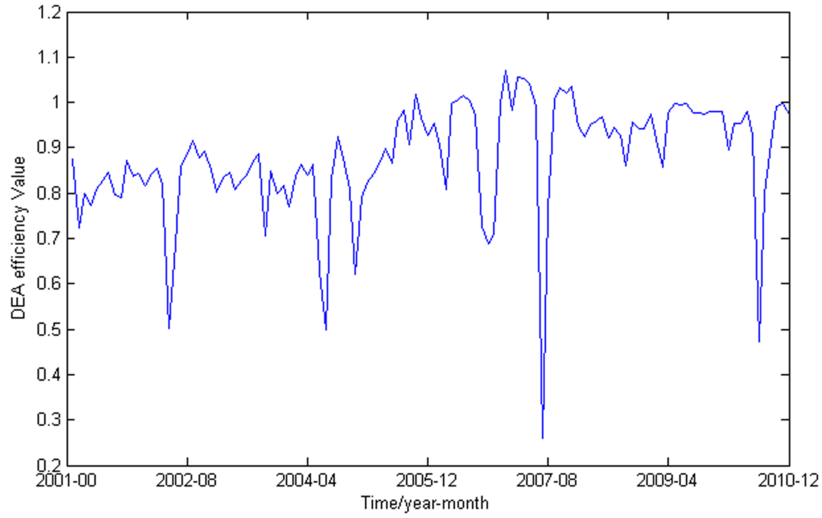

Figure 7. Monthly DEA efficiency values of plant 1 from 2001 to 2010 based on the improved DEA cross-model.

more accurate descriptions of the productivity change of various plants over time, excluding the subjective variable effects of crude, steam, fuel, water, and electricity, to further refine the reasons of efficient production analyzed by DEA from the technical efficiency change (TEFCH), technological progress, and scale efficiency change (SCH).

4.1. Malmquist Productivity Index Management Based on Improved DEA Cross-Model. Identification of each one of the components of the Malmquist Index is useful to understand the causes of the changes in productivity for each one of the DMUs, and for the industry as a whole. Another aspect that is important for the analysis is the identification of the DMUs that have been innovated from one period to another.[46]

The Malmquist index allows the technological change to be separated from the efficiency change, and is consistent with the method of DEA efficiency estimation. The adjacent Malmquist index and base-period Malmquist index are two types of Malmquist index. The adjacent Malmquist index does not need to consider the change of objective technology relative to the base period.

Because it obeys periodic relationships, the base-period Malmquist index may be more suitable for static efficiency analysis. However, if the selected base period is not representative, it may lead to serious problems in the results. The choice of base period often has certain arbitrariness.

On the basis of the technology of constant return to scale (CRS), Fare, Grosskopf, Norris, and Zhang (hereafter FGNZ) (1994) gave the decomposition of productivity changes.[30] The Malmquist index can be defined as the ratio of the period t technology (written as M_{CRS}^{t}) and the period $t+1$ technology (written as M_{CRS}^{t+1}).

$$M_{\mathrm{CRS}}^{t} = \frac{D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t)}{D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1})}, \quad \text{or} \quad M_{\mathrm{CRS}}^{t+1} = \frac{D_{\mathrm{CRS}}^{t+1}(x_A^t, y_A^t)}{D_{\mathrm{CRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})} \tag{8}$$

with time t as the reference technology, M_{CRS}^{t} measures the increase in production efficiency between the time t and $t+1$. To avoid the arbitrariness of selecting a reference technology, the Malmquist index can be defined as the geometric mean of M_{CRS}^{t} and M_{CRS}^{t+1}:

$$\begin{aligned} M_{\mathrm{CRS}}(x_A^{t+1}, y_A^{t+1}, x_A^t, y_A^t) &= [M_{\mathrm{CRS}}^{t} \cdot M_{\mathrm{CRS}}^{t+1}]^{1/2} \\ &= \left[\frac{D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t)}{D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1})} \cdot \frac{D_{\mathrm{CRS}}^{t+1}(x_A^t, y_A^t)}{D_{\mathrm{CRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})}\right]^{1/2} \end{aligned} \tag{9}$$

For the input-oriented DEA, there is the following DEA calculation based on CCR, that is, CRS:

$$\begin{cases} D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t) = \min \theta, \\ \sum_{i=1}^{n} \lambda_i x_{ji}^t \le \theta x_{jA}^t, \quad j = 1, 2, ..., m, \\ \sum_{i=1}^{n} \lambda_i y_{ri}^t \le y_{rA}^t, \quad r = 1, 2, ..., s, \\ \lambda_i \ge 0, \quad i = 1, 2, ..., n; \quad A = 1, 2, ..., n \end{cases} \tag{10}$$

When introducing slack variables, the above model can be expressed as

$$\begin{cases} D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^t + s^{i-} = \theta x_{jA}^t, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^t - s^{r+} = y_{rA}^t, \quad r = 1, 2, ..., s \\ \lambda_i \ge 0, \quad i = 1, 2, ..., n, \\ s^- \ge 0, \quad s^+ \ge 0, \quad A = 1, 2, ..., n \end{cases} \tag{11}$$

Then the second step of the DEA cross-model formula for solving $D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t)$ is as follows:

$$\begin{cases} \min y_k^t u \\ y_j^t u - x_j^t v \le 0, \quad j = 1, 2, \cdots, n, \\ y_i^t u = E_{ii} x_i^t v, \quad x_k^t v = 1, \\ u \ge 0, \quad v \ge 0 \end{cases} \tag{12}$$

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As mentioned in eq 7, $\varepsilon = 10^{-6}$. s_t^- and s_t^+ are introduced as slack variables. θ denotes the valid values for decision-making units. Similarly we get

$$\begin{cases} D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1}) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^{t} + s^{i-} = \theta x_{jA}^{t+1}, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^{t} - s^{r+} = y_{rA}^{t+1}, \quad r = 1, 2, ..., s \\ \lambda_i \geq 0, \quad i = 1, 2, ..., n, \\ s^- \geq 0, s^+ \geq 0, \quad A = 1, 2, ..., n \end{cases} \tag{13}$$

Then the second step of the DEA cross-model formula for solving $D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1})$ is as follows:

$$\begin{cases} \min y_k^t u \\ y_j^t u - x_j^t v \leq 0, j = 1, 2, \cdots, n, \\ y_i^t u = E_{ii} x_i^t v, \quad x_k^t v = 1, \\ u \geq 0, v \geq 0 \end{cases} \tag{14}$$

$$\begin{cases} D_{\mathrm{CRS}}^{t+1}(x_A^{t}, y_A^{t}) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^{t+1} + s^{i-} = \theta x_{jA}^{t}, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^{t+1} - s^{r+} = y_{rA}^{t}, \quad r = 1, 2, ..., s \\ \lambda_i \geq 0, \quad i = 1, 2, ..., n, \\ s^- \geq 0, \quad s^+ \geq 0, \quad A = 1, 2, ..., n \end{cases} \tag{15}$$

Then the second step DEA cross-model formula of solving $D_{\mathrm{CRS}}^{t+1}(x_A^t, y_A^t)$ is as follows:

$$\begin{cases} \min y_k^{t+1} u \\ y_j^{t+1} u - x_j^{t+1} v \leq 0, \quad j = 1, 2, \cdots, n, \\ y_i^t u = E_{ii} x_i^t v, \quad x_k^{t+1} v = 1, \\ u \geq 0, \quad v \geq 0 \end{cases} \tag{16}$$

By the CCR projection formulas:

$$\begin{cases} \hat{x}_{j0} = \theta_0^* x_{j0} + s_t^{i-*} = \sum_{i=1}^{n} x_{ji} \lambda_i^*, \\ \quad i = 1, 2, \cdots, m \\ \hat{y}_{r0} = y_{r0} - s_t^{r+*} = \sum_{i=1}^{n} y_{ri} \lambda_i^*, \quad r = 1, 2, \cdots, s \end{cases} \tag{17}$$

where $\hat{x}_{i0} \leq x_{i0}$ and $\hat{y}_{r0} \leq y_{r0}$ correspond to the coordinate origin of the efficient frontier, which is used to evaluate the effectiveness of DMU_0.

FGNZ decomposed M_{CRS} $(x_A^{t+1}, y_A^{t+1}, x_A^t, y_A^t)$ into a technical efficiency change (TEFCH) and a technological change (TECHCH) as follows:

$$\mathrm{TFFCH} = \frac{D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t)}{D_{\mathrm{CRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})} \tag{18}$$

$$\mathrm{TECHCH} = \left[\frac{D_{\mathrm{CRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})}{D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1})} \cdot \frac{D_{\mathrm{CRS}}^{t+1}(x_A^{t}, y_A^{t})}{D_{\mathrm{CRS}}^{t}(x_A^{t}, y_A^{t})}\right]^{1/2} \tag{19}$$

The Malmquist Index >1 (<1) indicates productivity growth (decrease). TEFCH > 1 (<1) indicates technical efficiency enhanced (reduced). And TECHCH > 1 (<1) indicates technology improved (degraded). Meanwhile, the TEFCH is expressed as the productivity of catching up production limits (the catch-up effect) and the TECHCH is expressed as the change of placement of production limits (the frontier-shift or boundary shift).

In 1997, to allow for some enterprises that do not meet the constant returns to scale (CRS), Ray-Desli used variable returns to scale (VRS) as a technology benchmark to decompose the Malmquist Index. Accordingly, the input-oriented Malmquist Index can be decomposed into pure efficiency change (PEFFCH) and pure technological change (PTECHCH), as well as the scale of change (SCH) of three sections, and they are

$$M_{\mathrm{CRS}}(x_A^{t+1}, y_A^{t+1}, x_A^t, y_A^t) = \mathrm{PEFFCH} \cdot \mathrm{PTECHCH} \cdot \mathrm{SCH} \tag{20}$$

where

$$\mathrm{PEFFCH} = \frac{D_{\mathrm{VRS}}^{t}(x_A^t, y_A^t)}{D_{\mathrm{VRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})} \tag{21}$$

$$\mathrm{PTECHCH} = \left[\frac{D_{\mathrm{VRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})}{D_{\mathrm{VRS}}^{t}(x_A^{t+1}, y_A^{t+1})} \cdot \frac{D_{\mathrm{VRS}}^{t+1}(x_A^{t}, y_A^{t})}{D_{\mathrm{VRS}}^{t}(x_A^{t}, y_A^{t})}\right]^{1/2} \tag{22}$$

$$\mathrm{SCH} = \left[\frac{D_{\mathrm{CRS}}^{t}(x_A^t, y_A^t) D_{\mathrm{VRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})}{D_{\mathrm{VRS}}^{t}(x_A^t, y_A^t) D_{\mathrm{CRS}}^{t+1}(x_A^{t+1}, y_A^{t+1})} \cdot \frac{D_{\mathrm{CRS}}^{t+1}(x_A^t, y_A^t) D_{\mathrm{VRS}}^{t}(x_A^{t+1}, y_A^{t+1})}{D_{\mathrm{VRS}}^{t+1}(x_A^t, y_A^t) D_{\mathrm{CRS}}^{t}(x_A^{t+1}, y_A^{t+1})}\right]^{1/2} \tag{23}$$

PEFFCH compares the distinction between the enterprises cycle from the period t to $t + 1$ and the VRS frontier. If PEFFCH > 1, the efficiency value of the enterprise is closer to the frontier in the period $t + 1$. PTECHCH measures the change of the VRS frontier between the period t and period $t + 1$ relative to the operating point of the enterprise itself. If the operating point in the period t, relative to the period frontier, is further from the frontier of the period $t + 1$, it means the frontier moved left and that technology has been improved. Similarly, the operating point in the period $t + 1$ is also enhanced. SCH is expressed as the scale economy of enterprise, if SCH > 1, the scale of enterprise is more appropriate in the period $t + 1$ relative to the period t.

Similarly, if a decision-making unit about the inputs and outputs of the CCR model is efficient, then it must be efficient about the inputs and outputs of the BCC model as well. Therefore, the BCC model (added slack variables) of Malmquist (VRS) is that the above CCR model added the constraint condition $\sum_{i=1}^{n} \lambda_i = 1$, $D_{\mathrm{VRS}}^t(x_A^t, y_A^t)$, $D_{\mathrm{VRS}}^t(x_A^{t+1}, y_A^{t+1})$, $D_{\mathrm{VRS}}^{t+1}(x_A^t, y_A^t)$ and can be calculated as follows:

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$$\begin{cases} D_{\mathrm{VRS}}^{t}(x_A^t, y_A^t) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^t + s^{i-} = \theta x_{jA}^t, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^t - s^{r+} = y_{rA}^t, \quad r = 1, 2, ..., s \\ \lambda_i \geq 0, \quad i = 1, 2, ..., n, \\ \sum_{i=1}^{n} \lambda_i = 1 \\ s^- \geq 0, \quad s^+ \geq 0, \quad A = 1, 2, ..., n \end{cases} \tag{24}$$

$$\begin{cases} D_{\mathrm{VRS}}^{t}(x_A^{t+1}, y_A^{t+1}) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^t + s^{i-} = \theta x_{jA}^{t+1}, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^t - s^{r+} = y_{rA}^{t+1}, \quad r = 1, 2, ..., s \\ \lambda_i \geq 0, \quad i = 1, 2, ..., n, \\ \sum_{i=1}^{n} \lambda_i = 1 \\ s^- \geq 0, \quad s^+ \geq 0, \quad A = 1, 2, ..., n \end{cases} \tag{25}$$

$$\begin{cases} D_{\mathrm{VRS}}^{t+1}(x_A^t, y_A^t) = \min[\theta - \varepsilon(e_1^{\mathrm{T}} s^- + e_2^{\mathrm{T}} s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji}^{t+1} + s^{i-} = \theta x_{jA}^t, \quad j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri}^{t+1} - s^{r+} = y_{rA}^t, \quad r = 1, 2, ..., s \\ \lambda_i \geq 0, \quad i = 1, 2, ..., n, \\ \sum_{i=1}^{n} \lambda_i = 1 \\ s^- \geq 0, \quad s^+ \geq 0, \quad A = 1, 2, ..., n \end{cases} \tag{26}$$

And the second step to solve the model formula of DEA cross-model for the Malmquist Index is the same to the second step of solving the CCR of DEA (CRS).

In addition to the advantages of DEA itself, the Malmquist Index based on DEA also has the advantages of not needing inputs and outputs information, strong adaptability, ease of calculation and so on. However, the input-oriented DEA model of the MPI shows that the conventional DEA model calculation cannot distinguish effective decision-making units good or bad, so the aim of this article is to solve MPI on the basis of the improved DEA model, by solving Malmquist CRS and VRS by CCR of the improved DEA cross-model, that is, eq 11, eq 13, eq 15 and the related calculations.

4.2. Performance Analysis of China Ethylene Plants over Time. By calculating the same input−output data as in the above analysis for 19 nationwide plants, we can obtain the TFPCH, the TEFCH for measuring efficiency level changing over the same period technology, the TECHCH for measuring technological progress, the PEFFCH for management level progress, the PTECHCH for measuring technological progress, and the SCH for scale changing over the same period technology by eqs 18, 19, and 21−23. The Malmquist Index values based on CRS and VRS of various plants in the period 2008−2009 are shown in Table 2.

As is shown in Table 2, the total production efficiency indices (TFPCH) of all plants are greater than 1, which indicates that the productivity of various plants has improved from 2008 to 2009. Both the TEFCHs and PEFFCHs of 13 plants are greater than 1, indicating that the technical efficiency of these plants is enhanced. Additionally, for plant 11, the TECHCH of the plant is greater than 1 and the PTECHCH of this plant is also greater than 1, indicating that the plant technology is improved. Similarly, when both the PTECHCH and the TECHCH are less than 1, these plants technologies are degraded. The SCHs of 11 plants are greater than 1, indicating that enhancement of the scale economies of these plants help to improve the productivity.

Among these plants, the efficiency values calculated by the DEA cross-model show that the efficiency values of plant 6 and plant 8 are the worst, and plant 11 and plant 13 are the highest. However, based on the MPI calculated by the DEA cross-model, plant 6 and plant 8 have a higher productivity efficiency. The total productivity efficiency values of plant 11 and plant 13 are the lowest. The main energy efficiency data of the four plants in 2008 are shown as Table A.2 (see Table A.2 in Supporting Information), and the energy efficiency data of all plants in 2009 are shown as Figure 1.

As shown in Supporting Information Table A.2 and Figure 1, when the DEA cross-model is used to calculate the energy efficiency value of each plant, it only considers the energy efficiency situation of each plant in the year. The total productivity efficiency values calculated by Malmquist dynamically compare the technological efficiency, technological change, and scale change of each plant. For plant 6 and plant 8, the total productivity values rank first in the whole industry. Their EFFCH and TECHCH indices are large, which indicates that they have a large technological change. Their SCHs decrease, indicating that the scales reduce when the technologies improve. If we further enhance the energy efficiency of plant 6 and plant 8, we can improve their scale economy and increase production. For plant 11 and plant 13, the slight increase of PEFFCH and SCH make their productivity improve a little, but their total productivity ranks last for the whole industry, which indicates that their productions are basically saturated and the indices have little variation space. It can enhance their technology or improve advanced technology to raise the energy efficiency of plant 11 and plant 13. According to the analyses above, each Malmquist index that is greater than 1 is conducive to increase productivity. On the basis of the situation that different plants can maintain the indices greater than 1 unchanged, it can increase Malmquist indices that are relatively weak or less than 1 to improve the energy efficiency of ethylene.

Similarly, the Malmquist Index values based on CRS and VRS of various plants in the period 2009−2010 are shown in Table 3.

It can be seen from Table 3 that only total production efficiency indices (TFPCH) of plant 1, plant 9, plant 10, plant 14, plant 17, and plant 18 are slightly greater than 1, which indicates that these plant productivities improved, but the improvements are not great enough for ethylene production. The TEFCHs and PEFFCHs of 16 plants are greater than 1, indicating that the technical efficiencies of these plants are enhanced. Moreover,

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Table 2. Malmquist Index Values of Various Plants in the Period 2008−2009[a]

plant	year	TFPCH	TEFCH	TECHCH	PEFFCH	PTECHCH	SCH
plant 6	2009	1.3276(1)	1.1037(3)	1.2029(5)	1.1662(2)	1.2962(4)	0.8783(18)
plant 5	2009	1.2548(2)	0.9842(17)	1.275(1)	0.9783(13)	1.4144(1)	0.9068(17)
plant 8	2009	1.2442(3)	1.0388(7)	1.1977(6)	1.0399(7)	1.2457(6)	0.9605(15)
plant 3	2009	1.2356(4)	0.9913(15)	1.2464(3)	0.974(15)	1.3458(2)	0.9426(16)
plant 10	2009	1.2241(5)	1.0067(11)	1.216(4)	1.0728(3)	1.303(3)	0.8757(19)
plant 2	2009	1.1988(6)	0.9589(19)	1.2502(2)	0.9336(19)	1.2822(5)	1.0015(11)
plant 19	2009	1.1869(7)	1.0143(10)	1.1702(7)	0.9853(12)	1.2356(7)	0.9749(14)
plant 4	2009	1.1626(8)	1.0381(8)	1.1199(8)	1.0195(9)	1.1567(8)	0.9859(12)
plant15	2009	1.1559(9)	1.3199(1)	0.8757(19)	1.2853(1)	0.913(19)	0.9859(13)
mean	2009	1.1322	1.0386	1.0951	1.0288	1.118	0.9949
plant 9	2009	1.1115(10)	1.0303(9)	1.0788(10)	1.0024(11)	1.0555(11)	1.0505(2)
plant 17	2009	1.075(11)	1.118(2)	0.9615(18)	1.0524(6)	0.9282(18)	1.1005(1)
plant 7	2009	1.0655(12)	0.9853(16)	1.0813(9)	0.9613(18)	1.064(10)	1.0417(3)
plant 1	2009	1.0619(13)	1.0025(13)	1.0593(13)	0.9767(14)	1.0642(9)	1.0217(8)
plant 18	2009	1.0476(14)	1.0526(6)	0.9953(15)	1.0396(8)	0.977(15)	1.0315(7)
plant 12	2009	1.0455(15)	1.0572(5)	0.989(16)	1.057(5)	0.95(16)	1.0412(5)
plant 16	2009	1.0413(16)	0.9932(14)	1.0484(13)	0.968(16)	1.0333(13)	1.0411(6)
plant 14	2009	1.039(17)	0.9718(18)	1.0692(11)	0.9649(17)	1.0339(12)	1.0415(4)
plant 13	2009	1.0207(18)	1.0607(4)	0.9623(17)	1.0571(4)	0.9473(17)	1.0192(9)
plant 11	2009	1.013(19)	1.0054(13)	1.0075(14)	1.0136(10)	0.9964(14)	1.003(10)

[a]Note: The value in bracket is sorted value (ranking).

Table 3. Malmquist Index Values of Various Plants in the Period 2009−2010[a]

plant	year	TFPCH	TEFCH	TECHCH	PEFFCH	PTECHCH	SCH
plant 17	2010	1.0830(1)	1.0806(9)	1.0022(3)	1.0169(14)	1.0328(3)	1.0311(3)
plant 10	2010	1.0301(2)	1.1114(10)	0.9269(10)	0.9825(17)	0.9202(13)	1.1394(1)
plant 18	2010	1.0198(3)	1.0952(7)	0.9312(9)	1.0746(7)	0.9393(11)	1.0104(4)
plant 9	2010	1.0111(4)	1.0394(15)	0.9727(5)	1.0557(9)	0.9483(8)	1.0099(5)
plant 1	2010	1.0092(5)	1.1621(3)	0.8684(16)	1.1595(2)	0.8704(18)	1(10)
plant 14	2010	1.0029(6)	1.0753(11)	0.9327(8)	1.0622(8)	0.9404(10)	1.0041(8)
plant 4	2010	0.9963(7)	1.0431(14)	0.9552(7)	1.0288(12)	0.9922(5)	0.9761(13)
plant 16	2010	0.9963(8)	1.0209(16)	0.9759(4)	1.0185(13)	0.9702(7)	1.0082(6)
mean	2010	0.9898	1.0715	0.9288	1.0491	0.9512	0.9972
plant 2	2010	0.9872(9)	1.0951(7)	0.9015(14)	1.1157(4)	0.9038(16)	0.9791(12)
plant 15	2010	0.9870(10)	0.8709(19)	1.1334(1)	0.8615(19)	1.1389(1)	1.006(7)
plant 12	2010	0.9865(11)	0.9697(18)	1.0174(2)	0.9753(18)	1.0512(2)	0.9622(16)
plant 7	2010	0.9856(12)	1.0822(8)	0.9107(13)	1.1024(5)	0.9289(12)	0.9624(15)
plant 11	2010	0.9762(13)	1.054(13)	0.9262(11)	1.0395(10)	0.9725(6)	0.9657(14)
plant 3	2010	0.9760(14)	1.0666(12)	0.9151(12)	1.034(11)	0.9413(9)	1.0028(9)
plant 13	2010	0.9694(15)	1.0008(17)	0.9686(6)	1.0057(15)	1.003(4)	0.961(17)
plant 5	2010	0.9577(16)	1.1895(2)	0.8051(18)	1.1492(3)	0.8761(17)	0.9512(18)
plant 8	2010	0.9483(17)	1.2151(1)	0.7804(19)	1.1655(1)	0.825(19)	0.9862(11)
plant 6	2010	0.9431(18)	1.1069(5)	0.852(17)	0.9977(16)	0.9055(15)	1.044(2)
plant 19	2010	0.9404(19)	1.0799(10)	0.8708(15)	1.0879(6)	0.9136(14)	0.9462(19)

[a]Note: The value in bracket is sorted value (ranking).

TECHCHs and PTECHCHs of 15 plants are less than 1, which means these plant technologies are degraded, causing the productivity (TFPCH) of these plants to be relatively low at the same time. The SCHs of 10 plants are greater than 1, indicating the scale economies of these plants are improved and the other plants scale economies are reduced.

In 2009 and 2010, the efficiency values of these plants calculated by the DEA cross-model show that the energy efficiency of plant 15 is relatively low while that of plant 12 is relatively high. The energy efficiency changes of these plants in the physical amount of production can be obtained by the energy efficiency data in Figure 1 and Figure 2. However, on the basis of the MPI analysis of plant 15 and plant 12, their total productivity indexes are basically the same. Their TECHCHs and PTECHCHs are relatively large, ranking first in the entire industry. Their TEFCHs and PEFFCHs rank last for the whole industry leading to total production efficiencies slightly less than 1 and the whole industry level. If we further enhance the energy efficiency of the both plants, we can increase the catch-up effect and level of technical management. Similarly, Malmquist indices that are greater than 1 have reached the optimized state, and energy efficiency indices that are less than 1 have greater impact on productivity, so different plants improve the worst MPI to enhance ethylene productivity and energy efficiency.

Table 2 and Table A.2 show that the TEFCH and the PEFFCH have the same variation trend, and the PTECHCH and the TECHCH have also the same trend. From 2008 to 2009, all plants' ethylene production efficiencies increase, indicating that they have the space for improvement in technology or scale. From 2009 to 2010, ethylene plant productivities under different technologies and different scales rise, because various plants enhance technical efficiency or improvements in technology and scale are not the same. If each plant focused on technology improvement in the previous year, there would be an increase of improvement on the technical efficiency or scale in the next year, which is consistent with the improvement direction described by Sinopec and other ethylene plants from 2008 to 2010.[1,37,38] Most of the plants in the ethylene production industry use Lummus-technology that improves technical efficiency and scale change, while fewer plants use TPL technology that improves technological change. By the analysis of various plants from 2008 to 2010, in the future ethylene production, the production analysis of ethylene plants under different technologies and different scales can be obtained according to the ethylene production indices of the prior year. Plants should pay attention to technological change when enhancing scale, as well as to ethylene production technological change when enhancing technical efficiency.

5. CONCLUSION

This paper proposed an improved DEA cross-model to calculate efficiency values of production plants to solve the inadequacies of the conventional DEA model. The problem with regards to low discrimination has been overcome by proposed improved DEA cross-model efficaciously that mitigates the deficiency that the improvement direction of ineffective decision-making units cannot be obtained by the conventional DEA cross-model.

On the other hand, the dynamic technical efficiency change, the technological change, pure technical efficiency change, pure technological change, scale efficiency change and the total factor productivity change of MPI, which comprehensively consider various input and output factors, are calculated by the improved DEA cross-model. Objective performance indices for different plants can be obtained by MPI in order to reveal the performance status of different China ethylene plants. The dynamic efficiency of the ethylene industry is analyzed consistently. The proposed method has overcome the shortcomings of the subjectivity of various efficiency index weights in the past efficiency evaluation.

An efficiency analysis of ethylene production plants was made, which objectively shows the ethylene performance trends of ethylene production plants under different technologies, pointing out the opportunity and direction of energy saving to help ethylene production enterprises further enhance improvement measures. It proves the validity and applicability of the method.

In our further studies, we will separate inputs into energy and nonenergy inputs and incorporates desirable (good) outputs and undesirable (bad) outputs for the performance evaluation of China ethylene plants. Moreover, we will build a computational framework of DEA nonradial measurement and radial measurement for time-series evaluations to calculate the global MPI. Furthermore, the proposed method can be applied to performance analysis of other process plants.

■ ASSOCIATED CONTENT

Ⓢ Supporting Information

Self-evaluation efficiency values of various plants in 2010; main input−output data of ethylene production of plants 6, 8, 11, 13 in 2009. This material is available free of charge via the Internet at http://pubs.acs.org.

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Notes

The authors declare no competing financial interest.

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