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Energy efficiency analysis based on DEA integrated ISM: A case study for Chinese ethylene industries

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ABSTRACT

The petrochemical industry evaluation is affected by numerous factors. Many previous studies proposed a use of data envelopment analysis (DEA) as a methodology for energy efficiency analysis in the petrochemical industry. However, excessive decision-making units (DMUs) of DEA model result in difficulties in evaluation and comparison of the different DMUs. In this paper, a new energy analysis framework of petrochemical industrial processes based on DEA integrated interpretative structural model (ISM) is proposed. The ISM method is brought up based on the partial correlation coefficient method to find the main factors and basic reasons that affect the energy consumption of the ethylene production system, which serve as the inputs of the DEA. Meanwhile, ethylene, propylene and C4 productions of the ethylene production system sever as the outputs of the DEA. Then the fractional DEA model is solved by using the linear programming method. The proposed evaluation method can overcome the shortcomings of the DEA model mentioned above, and also is able to reflect the effectiveness of the DMUs and guide the improvement directions of the ineffective DMUs based on slack variables. Our approach is applied in the energy efficiency analysis of Chinese ethylene industry in the petrochemical field. The empirical results show that the proposed energy consumption analysis method is valid and efficient in improvements of energy efficiency in ethylene production systems.

1. Introduction

In recent years, energy conservation and emission reduction is one of the top topics focused on by all countries in the world. In particular in petrochemical industry, energy efficiency is a means to reach both environmental and economic goals. Meanwhile, the ethylene industrial level plays an important role in evaluating the industrial development level of a country. According to the statistics, China Petrochemical Corporation's ethylene production was 9475 kt/a, and the average fuel plus power consumption (standard oil) was 579.59 kg per ton of ethylene produced in 2012 (Zhang and Liu, 2013).Those of China National Petroleum Corporation was 5110 kt/a and 628.6 kg per ton of ethylene produced standard oil in 2012, respectively (Ji et al., 2013). Their energy efficiency is far lower than that of the advanced countries. Meanwhile, the energy consumption cost of ethylene production plants took up more than half of the operation cost (Tao and Patel, 2006). Therefore, studying about the energy efficiency analysis of ethylene industries is beneficial for both the environment and the sustainable development of the Chinese economy.

Currently, the mean method and optimal index method to analyze energy efficiency are commonly used by enterprises (Baileya et al., 2008). Because the indicators and influencing factors of energy efficiency values have different meanings to energy efficiency indicators, the two methods cannot introduce energy-saving knowledge into energy efficiency analysis and are not able to provide the energy efficiency benchmark of optimal factors and indices to guide the actual state of energy efficiency analysis. Although energy efficiency analysis of ethylene plants based on the data fusion method has obtained better performance. However, the method did not take the impact factors of energy consumption indicators into account (Geng et al., 2010a, 2010b). Additionally, Zhang and Rong (2010) optimized fuel gas scheduling in refinery to achieve energy cost reduction and cleaner production by the fuzzy possibilistic programming (FPP) method. Sheng (2010) and Zhou et al. (2012) optimized the operation of cracking furnace and recovered the cold capacity from ethylene to reduce

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the energy consumption of ethylene plants. However, the economic cost of reforming industry plants did not taken into consideration. In allusion to the disadvantages of existed energy efficiency analysis of ethylene industry in China, the paper specifically proposes the method combining data envelopment analysis (DEA) with interpretative structural model (ISM) to analysis energy efficiency of the ethylene product system.

The remainder of this paper is organized in the following manner. Section 2 introduces the research status of energy efficiency in ethylene plants with DEA and ISM. Sections 3 and 4 provides the details of the DEA and the ISM methods, respectively. The energy efficiency analysis framework and process based on DEA integrated ISM in ethylene production industry are described in Section 5. Section 6 presents a case study about the energy efficiency analysis of ethylene production industry based on DEA integrated ISM. Finally, the conclusions are given in Section 7.

2. Literature review

In 1978, the DEA method was firstly proposed by the famous operational researchers Charnes, Cooper and Rhodes. They used it to make 'production apartment', which had multiple inputs and multiple outputs, both 'sizeable effective' and 'technological effective'. Meanwhile, the collinearity of input-output indicators (highly relevant) would not affect the stability and reliability of the DEA (Doyle and Green, 1994). Cook and Seiford (2009) provided a brief sketch of the DEA that have emerged over the past three decades. The application of DEA turned out to be much satisfactory and effective (Wei, 2000), especially in the petrochemical industry. Yang and Pollitt (2009) used six DEA-based performance evaluation models to investigate the performance of Chinese coal-fired power plants. Sueyoshi et al. (2010,2013) studied the DEA approach and the DEA window analysis for environmental assessment in a dynamic time shift to evaluate the operational, environmental and both-unified performance of coal-fired power plants, respectively. Zarandini and Sheikhnabi (2012) analysis and rankings of Iran power plants using mathematical models of DEA with the factor of the type of chemical consumption fuel. Bi et al. (2014) investigated the relationship between fossil fuel consumption and the environmental regulation of China's thermal power generation using the DEA approach. Sueyoshi and Goto (2014) analyzed energy utilizations and environmental protections of Japanese chemical and pharmaceutical firms by the DEA radial measurement approach. Han et al. (2015a, 2015b) used the Malmquist production index (MPI) method based on DEA cross-model and fuzzy DEA cross-model to investigate the performance efficiency of Chinese ethylene plants. However, the quantities of input and output indicators and the number of samples had a great influence on the results of DEA analysis (Ruggiero, 2005; Cooper et al., 2006). The DEA model can lead to the situation that more than one-third of efficiency values are set to 1, which means the efficiency discrimination is poor. Moreover, in order to avoid the drawbacks of the DEA and get the maximum efficiency analysis index of each decision-making unit, the DEA integrated ISM method is proposed to analyze the energy efficiency index of the ethylene production process.

In 1973, Warfield developed the interpretive structural model (ISM) to analyze the complex system. Kuo et al., (2010), Faisal (2010), Chandramowli et al. (2011) and Talib et al. (2011) analyzed these barriers into a hierarchical structure of the product service system, the supply chains and the total quality management by the ISM. Govindan et al. (2012) used the ISM to analyze the third party reverse logistics provider. Attri et al. (2013) discussed key concepts of ISM approach. Wan and Pan (2014) analyzed the top 10 risk factors of GZA project implementation based on the ISM to enhance the success rate of GZA project implementation. Zhang et al. (2015) employed the power system to analyze the relationship among the factors having impacts on the network reconfiguration base on the ISM. The research results mentioned above proved the practicality and effectiveness of ISM. The ethylene product system is a complex industrial process with a lot of variables thus ISM can be used to construct a hierarchy model based on energy consumption data. It can utilize easily accessible monthly operational data to establish the reliable variable correlations, which can make the energy consumption analysis more scientific and reliable. At the same time, the complexity of modeling process in an ethylene product system can be avoided.

The initial step to establish an ISM is to create an adjacency matrix using experts' experience mostly. But its shortcoming is subjectivity and inconsistency. In time series data analysis, Yu et al. (2007) found out that the partial correlation function can be more realistic to reflect the correlation relationship among variables. Fan et al. (2010) used the correlation coefficient method to verify the efficiency of Signed Directed Graph (SDG) model. Vargha et al. (2013) discussed interpretation problems of the partial correlation with nonnormally distributed variables. Wang et al. (2013) using the partial information correlation coefficient (PICC) method to effectively reduce false alarms in defect detection. Koesterke et al. (2014) using the optimized partial correlation coefficient with information theory algorithm to analyze the discovery of biological networks on Stampede's Xeon and Xeon Phi processors. Other researchers studied the partial correlation coefficients and achieved the positive results in the closed-loop optimal experiment, the permutation test and the copula function modeling and system fault detection (Bergsma, 2011; Kim et al., 2011; Chen et al., 2014). Therefore, based on the adjacency matrix of correlation coefficients and partial correlation coefficients, the reachability matrix can be built, and then the ISM would be obtained. Moreover, the ISM of energy consumption in the ethylene production system is constructed based on date-driven method considering the process knowledge and mechanism model.

First, by analyzing a large number of easily accessible monthly operational data and considering the complexity of the ethylene plant in modeling process, this paper proposes an effective approach using ISM based on the partial coefficients to analyze the main factors and basic reasons affecting the energy consumption of an ethylene product system. Then this paper uses DEA to analyze efficiency value of different plants under the same technology based on the main factors and basic reasons. At the same time, the model obtains the energy efficiency of the ethylene production plant to find the improvement direction of ineffective DMUs. Further, it can be used to evaluate and analyze energy efficiency in petroleum chemical plants reasonably, offering operation guidance for energy saving.

3. DEA with linear programming method

The *CCR* model is the first model of DEA analysis. Meanwhile, Compared with BCC, the efficient point of CCR model is "the absolute DEA effective" (Banker et al., 1984). In 1986, Charnes et al. established the new C^2WH-DEA model which reflects the preferences of the decision makers and the evaluation of the technology and scale, briefly as follows:

There are n supposed units or departments (namely decision-making units, abbreviated DMU). Each DMU has m inputs and s outputs, in which$x_j=(x_{1j},x_{2j},...,x_{mj})^T>0$, $y_j=(y_{1j},y_{2j},...,y_{sj})^T>0$ $(j=1,2,...,n)$, x_{ij}equals to inputs to ith input of DMU_{-j}, y_{rj}equals to outputs to rth output ofDMU_{-j} $(j=1,2,...,n;i=1,2,...,m;r=1,2,...,s.)$. And DMU_{-j0} has its corresponding input and output data of$x_0=x_{j0}$, $y_0=y_{j0}(1\le j0\le n)$. The C^2WH-DEA model for evaluating

DMU_{-j0} is shown in Eq. (1) as the fractional programming.

$$\begin{cases} \max \mu^T y_0 \\ v^T x_j - u^T y_j \in K, j = 1, 2, ..., n \\ u \in U - \{0\} \\ v \in V - \{0\} \end{cases} \tag{1}$$

where in, $v = (v_1, v_2, \ldots, v_m)^{\mathrm{T}}$, $u = (u_1, u_2, \ldots, u_s)^{\mathrm{T}}$, respectively represent weight coefficients of m inputs and s outputs, $U \subset R^m, V \subset R^s, K \subset R^n$, and $\ln tV \neq \varnothing, \ln tU \neq \varnothing$. The C^2WH-DEA model transformation formula for the fractional programming, proposed by Charnes and Cooper in 1962, is shown in Eq. (2) as follows.

$$\begin{cases} \max u^T y_0 = v^0, \\ v^T x_j - u^T y_j \geq 0, j = 1, 2, ..., n, \\ u^T x_0 = 1, \\ u \geq 0, v \geq 0 \end{cases} \tag{2}$$

The fractional model (C^2WH-DEA model) could be transformed into equivalent linear programming,

$$\begin{cases} \min \theta, \\ \sum_{j=1}^{n} x_j \lambda_j \leq \theta x_0, \\ \sum_{j=1}^{n} y_j \lambda_j \geq y_0, \\ \lambda_j \geq 0, j = 1, 2, ..., n, \theta \in E. \end{cases} \tag{3}$$

where in, $E$is a unit vector. We use the equation form of the dual model in Eq. (3) (with slack variables and the non-Archimedean infinitesimal ε), which is the input-oriented line of the DEA model, to get the Eq. (4) as follows.

$$\begin{cases} \min [\theta - \varepsilon(e_1^T s^- + e_2^T s^+)], \\ \sum_{i=1}^{n} \lambda_i x_{ji} + s^- = \theta x_{jA}, j = 1, 2, ..., m \\ \sum_{i=1}^{n} \lambda_i y_{ri} - s^+ = y_{rA}, r = 1, 2, ..., s \\ \lambda_i \geq 0, i = 1, 2, ..., n, \end{cases}$$
$$s^- \geq 0, s^+ \geq 0, A = 1, 2, ..., n \tag{4}$$

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, specific value of ε is set as large as possible. In this paper, in order to separate efficient and weakly efficient DMUs, we set $\varepsilon = 10^{-6}$ (Alirezaee, 2005; MirHassani and Alirezaee, 2005; Alirezaee and Khalili, 2006; Zhang et al., 2010), s_t^- ands_t^+ are the slack variables, $s_t^- = (s_t^{1-}, s_t^{2-}, ..., s_t^{m-})^T, s_t^+ = (s_t^{1+}, s_t^{2+}, ..., s_t^{r+})^{\mathrm{T}}$ are the redundancy amount of m input items and the shortfall of s output items respectively.$e_1^T = (1, 1, ..., 1) \in R^m, e_2^T = (1, 1, ..., 1)^T \in R^s$, θ is the efficiency values of the DMU_{-j0},which stands the efficiency of degree of inputs relative to outputs. Thus, if $\theta < 1$, $DMU_{-j0}$is DEA ineffective; if $\theta = 1$, DMU_{-j0} is effective or weak effective according to the establishment or not of the two constrained inequalities. All DMUs that are DEA effective constitute the production effective frontier. Moreover, the value of θ is the lower relative efficiency further from the production frontier (Han et al., 2014).

It can be seen from the above model that the efficiency values of the DEA is relative. Since the DEA model could describe the production frontier as long as multi-input and multi-output data are given, the accuracy of analysis results is easily affected by DMU input and output data and their precision. Thus, the input and output data need to be preprocessed to improve the accuracy of description of ethylene production frontier by the DEA model.

4. The ISM based on the partial correlation coefficients

The ISM model is based on the partial coefficient analysis among different elements. It can find out the real relationships among different variables and gets rid of influences of rest irrelevant variables, as well as removes the influences of subjective factors. Moreover, it will be systematically to build ISM through data-driven based analysis, because the procedure to build the adjacency matrix will be objective and consistent.

4.1. Modeling the partial correlation coefficient matrix

Because the correlation coefficient based approach only considers the relationship between two variables, it is seldom used to infer the inner relationship between variables directly. And in practical, other factors causing the relationship should also be considered. By contrast, the partial correlation relationship deducts or fixes the effect of other variables beside the relationship of two variables. It reflects the real linkages of different variables, which are evaluated by partial correlation coefficients (Zhang, 2009). The greater the absolute value of a partial correlation coefficient is, the stronger the relationship between both variables will be. Because of the ceteris paribus influence, it reflects the correlation between the dependent and independent variables, which has no units with the number between -1 and 1. Hence, we use the absolute value of it generally.

Let x_i (index$i = 1, 2, ..., m$) is the ith value of a variable$x$, then the correlation coefficient of $x_i$and y_i is

$$r_{xy} = \frac{\sum_{i=1}^{M} (x_i - \overline{x})(y_i - \overline{y})}{\sqrt{\sum_{i=1}^{M} (x_i - \overline{x})^2} \sqrt{\sum_{i=1}^{M} (y_i - \overline{y})^2}} \tag{5}$$

where, $\overline{x}$ is the mean value of x, $\overline{y}$ is the mean value of y.According to the Eq. (5), we can get the correlation coefficients matrix:

$$r = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1n-1} & r_{1n} \\ r_{21} & r_{22} & \ldots & r_{2n-1} & r_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ r_{m1} & r_{m2} & \ldots & r_{m-1n-1} & r_{mn} \end{bmatrix}_{m*n} \tag{6}$$

The inverse matrix is used to get the partial correlation coefficient matrix, that is, compute the correlation coefficient matrix firstly, and then get the inverse matrix.

The inverse matrix of r is c:

$$c = inv(r) = \begin{bmatrix} c_{11} & c_{12} & \ldots & c_{1n-1} & c_{1n} \\ c_{21} & c_{22} & \ldots & c_{2n-1} & c_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ c_{m1} & c_{m2} & \ldots & c_{m-1n-1} & c_{mn} \end{bmatrix}_{m*n} \tag{7}$$

$inv(r)$ denotes the inverse matrix of r, then the partial correlation coefficient between two variables is:

$$R_{ij} = -\frac{c_{ij}}{\sqrt{c_{ii} * c_{jj}}} \tag{8}$$

where, $i = 1, 2, ..., m; j = 1, 2, ..., m$.

There is a different definition about whether the partial correlation coefficient is related or not in different industries. In general, the relationship is shown in Table 1 corresponding to the scope of partial correlation coefficients (Zhang et al., 2005).

4.2. Modeling the ISM

R_{ij} is a positive number and greater than the threshold value, then$a_{ij}=1$ and $a_{ji}=0$, is the adjacency value of $x_i$tox_j $(i=1,2,\ldots,n;j=1,2,\ldots,n)$, otherwise, $a_{ij}=0$ and $a_{ji}=1$. The adjacency matrix is as follows:

$$A=\begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n-1} & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n-1} & a_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ a_{n1} & a_{n2} & \ldots & a_{n-1n-1} & a_{nn} \end{bmatrix}_{n*n} \tag{9}$$

Suppose

$$E=\begin{bmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & 0 & 1 \end{bmatrix}_{n*n} \tag{10}$$

is $n*n$identity matrix, then

$$A+E=(A+E)^2=\ldots=(A+E)^{n-1}=(A+E)^n \tag{11}$$

$R=(A+E)^{n-1}$,which is the reachability matrix of the adjacency matrix A.

$$R=\begin{bmatrix} R_{11} & R_{12} & \ldots & R_{1n-1} & R_{1n} \\ R_{21} & R_{22} & \ldots & R_{2n-1} & R_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ R_{n1} & R_{n2} & \ldots & R_{n-1n-1} & R_{nn} \end{bmatrix}_{n*n} \tag{12}$$

Defination 1. In the ith rowR_i $(i=1,2,\ldots,n)$ of reachability matrix$R$, if $R_{ij}=1(j=1,2,\ldots,n)$, then the element R_{ij} is added into the reachable set. The reachable set is expressed asS_i.

Defination 2. In the jth column R_i $(j=1,2,\ldots,n)$ of reachability matrix$R$, if $R_{ij}=1(i=1,2,\ldots,n)$, then the element R_{ij} is added into the first set. The first set is expressed asB_j.

The influencing factors can be stratified based on $S_j \cap B_j = S_j$, and then the highest level of factors L_1 is identified. The column and row corresponding with L_1 are removed from the reachability matrix$R$. By the same decision rules, L_2 $L_3 L_2 \ldots L_k$ can be identified. The last step is to establish the hierarchy model of ISM using each level of$L$.

The model of ISM based on partial correlation coefficient is described as follow:

Step 1: Build the correlation coefficients matrix$r$by Eqs. (5) and (6).
Step 2: Establish the partial correlation coefficients matrix using the inverse matrix of r getting from Eqs. (7) and (8).
Step 3: Transform the adjacency matrix$A$using Eq. (9), which is made of correlation coefficient thresholds to reachability matrix R using Eqs. (10) and (11).
Step 4: Get the advanced set and the reachable set of the reachability matrix R, and the first level of elements can be obtained by the definition of ISM.
Step 5: In the reachability matrix R, remove the corresponding row and column of the elements which included in the first level, and then rebuild the reachability matrix again, run back to step 3, the loop will not stop until there is no element in reachability matrix.

Table 1
The scope of partial correlation coefficient corresponding to relationships.

The scope of partial correlation coefficient	Relationship between both variables
$0 \le \|R_{ij}\| < 0.1$	No relationship
$0.1 \le \|R_{ij}\| < 0.3$	Low correlation
$0.3 \le \|R_{ij}\| < 0.5$	Medium correlation
$0.5 \le \|R_{ij}\| < 0.8$	Strong correlation
$0.8 \le \|R_{ij}\| \le 1$	Extremely strong

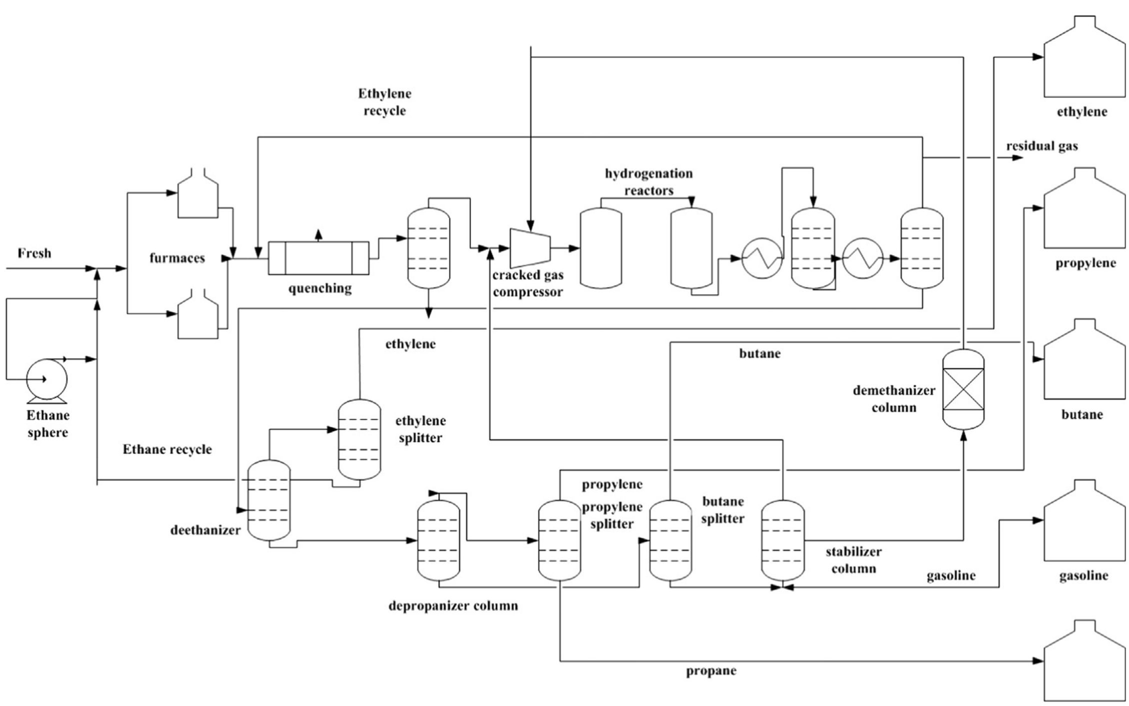

Fig. 1. A typical flowsheet of the ethylene plant.

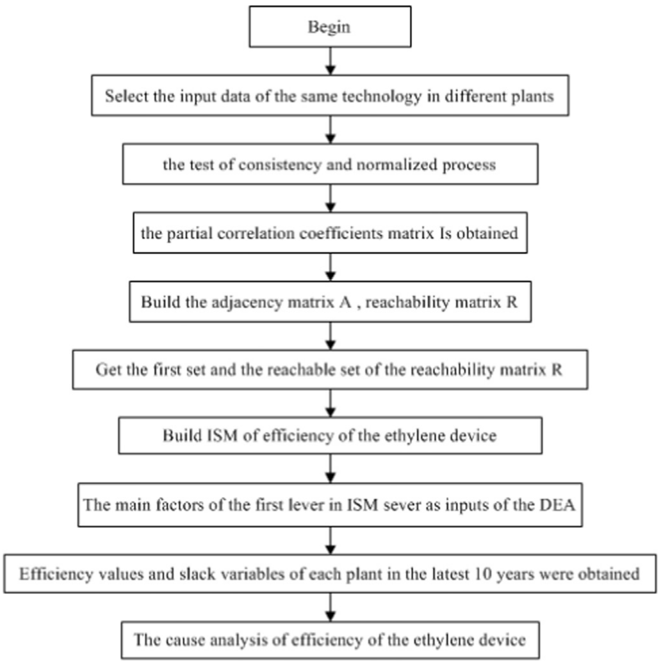

Fig. 2. Flowchart of energy efficiency analysis of ethylene production equipment based on DEA integrated ISM.

Step 6: Build ISM based on the elements from each level.

5. An energy efficiency analysis framework and process based on DEA integrating ISM in ethylene production industry

There are about seven common process technologies in Chinese ethylene product industries (Geng et al., 2012). In the article, the S&W front-end depropanization and front adding hydrogen technology is taken as an example to illustrate the effectiveness of the proposed method.

The ethylene production can be divided into two parts: cracking and separation. When a cracking furnace is running, a large number of fuels are needed to provide heat to the tube cracking reactions, and a Transfer Line Exchanger (TLE) produces a great amount of steam by recovering the waste heat. In order to make the raw material hydrocarbon finish the optimal cleavage reactions in a short time, and at the same time reduce coke, the steam should be injected when the hydrocarbon is fed into the cracking furnace.

The separation section mainly contains three parts: a rapid cooling, a compression and a separation part. The main energy consumption is the power consumption of compressor, the heat separation such as the consumption of steam, and cooling energy consumption of the compressor and the cold box. A typical flowsheet of the ethylene plant is shown in Fig. 1 as follows.

5.1. Energy boundary of ethylene product system

According to the statistics, the energy consumption fees are up to more than 50% of total cost for ethylene product process. The first factor affecting the overall energy consumption of the ethylene plant is the quality of raw material, the second is what cracking technology is adopted, the third is the separation process, and the last is the supporting facilities (public project, periphery project) (Wu et al., 2007). More than 70 percent of the total cost in ethylene production is taken by cracking materials (Naphtha, light diesel oil, raffinate, hydrogenation tail oil, carbon3, carbon4, carbon5 and other materials). The main energy types are included

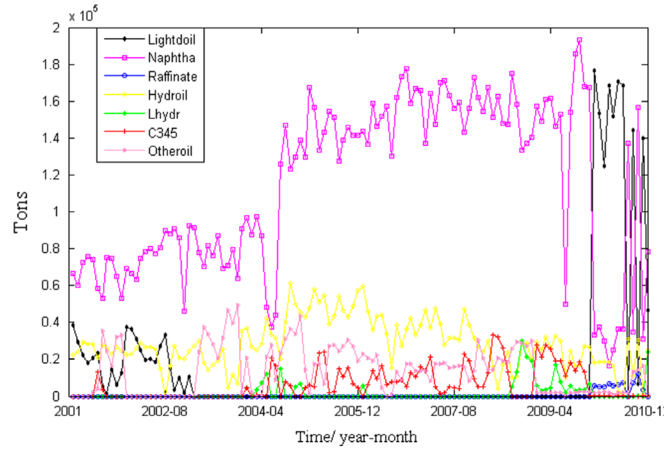

Fig. 3. The required crudes of one ethylene plant from 2001 to 2010.

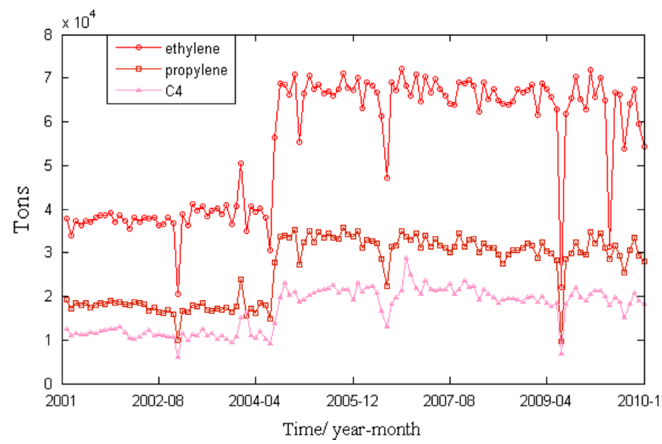

Fig. 4. The production of ethylene, propylene and C4 of one ethylene plant from 2001 to 2010.

in the ethylene utilization boundary (Geng et al., 2012) as follows: the water including the recycled water, the industrial water and the boiler feed water; the power (electricity); steams including the ultra-high pressure steam, the high pressure steam, the medium pressure steam and the low pressure steam; fuels including the fuel gas, the heavy oil and the light oil; N2 and the compressing air. Because of the lowest consumption of N2 and the compressing air among energy types, they were not taken into consideration when analyzing energy efficiency of ethylene product process.

5.2. Data preprocessing

Based on the factor analysis of energy consumption in the ethylene plant, in monthly actual production, the energy data are collected which contain several kinds of crude (Naphtha, light diesel oil (Lightdoil), Raffinate, hydrogenation tail oil (Hydroil), light hydrogenation tail oil (Lhydr), carbon3, carbon4, carbon5 (C345) and other force (Otheroil)), fuel (fuel gas (FG), light oil (LO) and heavy oil (HO)), steam (ultra-high pressure steam (SP), high pressure steam (HP), medium pressure steam (MP), low pressure steam (LP)), water (recycled water (RW), industrial water (IW), boiler feed water (BW)), electricity(E). These serve as the inputs, and the production of the main products ethylene, propylene and C_4 are taken as the outputs (Geng et al., 2010a, 2010b, 2012; Han et al., 2014).

Ethylene production data has complex nonlinear timing relationship, and includes noise and abnormal data, etc. And dimension for variables of timing data is generally different, which makes values of variables incomparable (Geng et al., 2010a). At

Table 2
The partial correlation matrix of the energy consumption data.

	PONA	FG	LO	HO	SP	HP	MP	LP	RW	IW	BW	E
PONA	−1.00	0.14	0.04	0.04	−0.07	−0.05	0.05	−0.04	0.05	0.05	−0.21	0.15
FG	0.14	−1.00	−0.38	−0.33	−0.28	−0.50	−0.24	−0.09	−0.38	0.11	0.27	−0.17
LO	0.04	−0.38	−1.00	−0.02	−0.06	−0.26	−0.24	0.06	−0.06	0.25	0.42	0.22
HO	0.04	−0.33	−0.02	−1.00	0.17	−0.10	−0.12	0.11	−0.24	0.02	−0.02	−0.03
SP	−0.07	−0.28	−0.06	0.17	−1.00	−0.80	−0.26	0.13	−0.05	0.07	0.17	−0.29
HP	−0.05	−0.50	−0.26	−0.10	−0.80	−1.00	−0.41	0.04	−0.25	0.18	0.37	−0.05
MP	0.05	−0.24	−0.24	−0.12	−0.26	−0.41	−1.00	0.08	0.08	0.10	−0.03	0.13
LP	−0.04	−0.09	0.06	0.11	0.13	0.04	0.08	−1.00	−0.16	0.13	−0.26	0.44
RW	0.05	−0.38	−0.06	−0.24	−0.05	−0.25	0.08	−0.16	−1.00	0.14	0.35	0.33
IW	0.05	0.11	0.25	0.02	0.07	0.18	0.10	0.13	0.14	−1.00	−0.08	−0.13
BW	−0.21	0.27	0.42	−0.02	0.17	0.37	−0.03	−0.26	0.35	−0.08	−1.00	0.16
E	0.15	−0.17	0.22	−0.03	−0.29	−0.05	0.13	0.44	0.33	−0.13	0.16	−1.00

Table 3
The reachability matrix of the energy consumption data.

	PONA	FG	LO	HO	SP	HP	MP	LP	RW	IW	BW	E
PONA	1	0	0	0	0	0	0	0	0	0	0	0
FG	0	1	0	0	0	0	0	0	0	0	0	0
LO	0	0	1	0	0	0	0	0	0	0	1	0
HO	0	0	0	1	0	0	0	0	0	0	0	0
SP	0	0	0	0	1	0	0	0	0	0	0	0
HP	0	1	0	0	1	1	0	0	0	0	0	0
MP	0	1	0	0	1	1	1	0	0	0	0	0
LP	0	0	0	0	0	0	0	1	0	0	0	1
RW	0	0	0	0	0	0	0	0	1	0	0	0
IW	0	0	0	0	0	0	0	0	0	1	0	0
BW	0	0	0	0	0	0	0	0	0	0	1	0
E	0	0	0	0	0	0	0	0	0	0	0	1

Table 4
The ISM model of the energy consumption data.

Variables	Reachable sets	First set	Intersection
PONA	PONA	PONA	PONA
FG	FG	FG,HP	FG
LO	LO,BW	LO	LO
HO	HO	HO,HP	HO
SP	SP	SP,HP	SP
HP	FG, SP,HP	HP,MP	HP
MP	HP,MP	MP	MP
LP	LP, E	LP	LP
RW	RW	RW	RW
IW	IW	IW	IW
BW	BW	LO,BW	BW
E	E	LP,E	E

the same time, it can be seen from the model above that efficiency of DEA is relative. The accuracy of analysis result is easily affected by multi-input and multi-output data of the ethylene plants and their precision. Thus, consistency test, normalized and uniform dimension disposal of units are applied to process the data. The following Eq. (13) is for the long-length data, and will lead to erroneous judgment for the short-length data (Geng et al., 2010a). But the long-length data could be tested according to Grubbs criterion (Zhang et al., 2001): if $T \geq T(n, \alpha)$, then $x_i$is eliminated, n denote the number of data and $\alpha$is the significant level.

$$T = \frac{|V|}{S} = \frac{|x_i - \bar{x}|}{S} \tag{13}$$

wherein,$\bar{x}$ and$S$express respectively the mean and variance, the value of $T(n, \alpha)$refers to literature Geng et al. (2012).

Based on characteristics of energy efficiency data of ethylene production plants, the general method to express its level is to convert measure units of energy consumption parameters of fuel, electricity, water and steam into uniform GJ. This conversion is based on Tables 3.0.2 and 3.0.3 from Energy Consumption Calculation Method of Petroleum Chemical Design (SH/T3110-2001) (State Economic and Trade Commission of the People's Republic of China., 2011). According to the feature of PONA, the crude oils are transformed to the PONA values. Because the PONA value not only reflects public cracking features for each kind of oil, but also can avoid the null value of the oil situation, additionally, it can help substitute overmuch raw material oil inputs with the single PONA value in order to reduce the evaluation index.

The general transformation method is by proportion. However, the described subjects of timing data need to be paid attention to. For the same subject, different variables make different interactions, some of which are positive as shown in Eq. (14) (Geng et al., 2012).

$$x_{ij}' = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{14}$$

While other variables are negative, the respective formula is shown in Eq. (15).

$$x_{ij}' = 1 - \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \tag{15}$$

in which$x_j^{\max} = \max\{x_{1j}, x_{2j}, ..., x_{tj}\}$, $x_j^{\min} = \min\{x_{1j}, x_{2j}, ..., x_{tj}\}$, $i = 1, 2, ..., t; j = 1, 2, ..., m$.

5.3. *The analysis process of the ethylene plant efficiency*

The process of ethylene production is considered as a multi-input and multi-output process. The abnormal and noise data made by the process could be rejected through consistency test, normalized and uniform dimension disposal of units. After data disposal, the multi-input and multi-output data can be sorted more accurately and objectively. Moreover, the precision of energy efficiency evaluation of ethylene production plants improves significantly by the DEA integrated ISM analysis. These works are able to demonstrate the methods of disposing feed costs for different plants under different production technologies, and the ways to improve energy efficiency and how to increase outputs. The energy efficiency analysis framework of ethylene production plants based on the DEA integrated ISM method is described as following:

Step 1: Select the input data of the same technology in different plants, and carry on data consistency test and uniform units' disposal by Eqs. (13)–(15).
Step 2: Build the correlation coefficients matrix$r$by Eqs. (5) and (6).

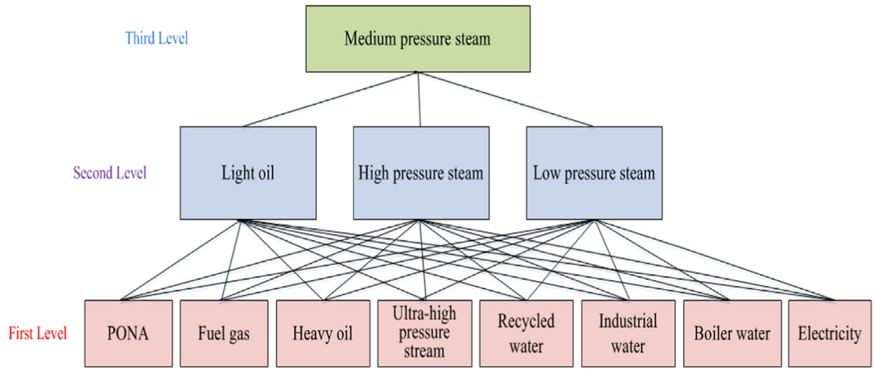

Fig. 5. The cause-effect of energy consumption of one technology based on the ISM model.

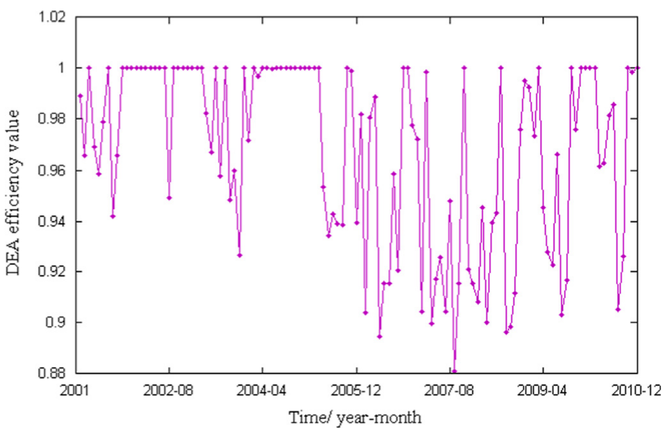

Fig. 6. The ethylene production efficiency values of one plant.

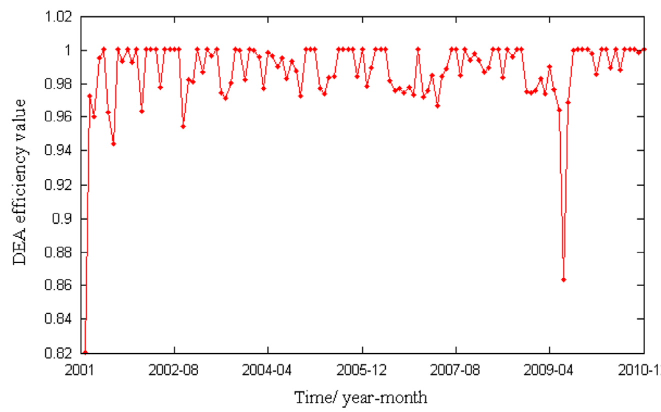

Fig. 7. The ethylene production efficiency values of another plant.

Step 3: Establish the partial correlation coefficients matrix using the inverse matrix of r getting from Eqs. (7) and (8).
Step 4: Transform the adjacency matrix A by Eq. (9), which is made of correlation coefficient thresholds to reachability matrix R by Eqs. (10) and (11).
Step 5: The ISM of this technology based on the elements from each level can be obtained by the definition of ISM.
Step 6: The main factors of the first lever in ISM sever as inputs of the DEA, and the yields of the main products ethylene, propylene and C4 are taken as outputs of the DEA.
Step 7: The ethylene production efficiency values and the slack variables of each plant in the latest 10 years were obtained by Eq. (4).
Step 8: Energy efficiency analysis of the efficiency and inefficiency month data of the ethylene plant.

Diagrammatically, Fig. 2 shows the whole process of DEA integrated ISM for analyzing the energy efficiency of ethylene industry.

6. Case study: the energy efficiency analysis of Chinese ethylene production industries

In order to embody the efficiency of Chinese ethylene production, it is important that the S&W front-end depropanization and front adding hydrogen technology is used in the empirical analysis. There are five ethylene plants in China under the S&W front-end depropanization and front adding hydrogen technology, which are Guangzhou, Lanhua, Maoming, Shanghai, and Yangba ethylene, and the monthly data of energy efficiency in the latest 10 years came largely from those nine plants. Fig. 3 shows the required crudes in one ethylene plant from 2001 to 2010. And Fig. 4 presents the production of ethylene, propylene and C_4 of one ethylene plant from 2001 to 2010.

First, the monthly data from five ethylene plants are taken to analyze the energy consumption of ethylene plant under the S&W front-end depropanization and front adding hydrogen technology, and the consistency test is used to remove outliers according to correlation Eq. (13). Second, the PONA value and normalization are used to get the uniformly unit, then to get the ethylene plant energy consumption data by different scales and different techniques. According to Eqs. (5)–(8), the partial correlation matrix is shown in Table 2.

In the ethylene production system, if correlation coefficients are obtained by energy-related materials of ethylene production such as raw materials, water, steam, electricity, fuel and so on, and the public project is greater than 0.3, then they can be called related. According to the characteristics of massive ethylene production data collected from those 19 plants in China in the latest 10 years, and better analyze the effect of the ethylene's productivity, the threshold of the partial correlation coefficient is determined as no less than 0.4, and then the value between two variables in the adjacency matrix is 1. If$R_{ij} \geq 0.4$, then$a_{ij}=1$ and $a_{ji}=0$, otherwise, if$R_{ij} \leq -0.4$, which is called negative correlation, then $a_{ij}=0$ and $a_{ji}=1$.

The reachability matrix R can be made in Table 3 through the analysis thresholds of related elements using Eqs. (9)–(12).

It can be seen from Table 3, the first reachability matrix of the energy consumption data can be obtained including all the elements. Low pressure steam has a direct impact on electricity, high-pressure steam has a direct impact on ultra-high pressure steam, light oil has a direct impact on boiler water and medium-pressure steam has a direct impact on fuel oil, ultra-high pressure steam, high-pressure steam.

Table 5
The slack variables of the plant from 2009 to 2010.

s^{1-}	s^{2-}	s^{3-}	s^{4-}	s^{5-}	s^{6-}	s^{7-}	s^{8-}	s^{1+}	s^{2+}	s^{3+}	θ	Times
0.00	0.00	0.00	0.23	72.63	0.17	0.00	0.02	0.00	1372.43	800.63	0.99	2009–01
0.00	0.00	0.00	0.49	14.64	0.01	0.00	0.05	0.00	969.65	0.00	0.97	2009–02
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2009–03
0.00	0.00	0.01	0.04	0.00	0.00	0.00	0.00	0.00	2482.99	1891.71	0.95	2009–04
0.00	0.04	0.02	0.26	48.31	0.01	0.00	0.00	0.00	2278.76	1579.43	0.93	2009–05
0.00	0.01	0.01	0.29	85.45	0.00	0.00	0.07	64.24	2445.07	0.00	0.92	2009–06
0.00	0.00	0.00	0.00	208.95	0.15	0.00	0.18	25715.84	13606.75	8202.31	0.97	2009–07
0.00	0.00	0.00	0.00	20.74	0.00	0.00	0.15	0.00	1503.73	487.92	0.90	2009–08
0.00	0.01	0.00	0.07	0.00	0.00	0.34	0.00	2349.43	3546.71	753.01	0.92	2009–09
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2009–10
0.00	0.01	0.00	0.63	92.62	0.00	0.00	0.15	3566.51	3510.23	241.79	0.98	2009–11
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2009–12
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2010–01
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2010–02
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2010–03
0.00	0.01	0.00	0.00	38.04	0.00	0.73	0.08	6091.35	3396.13	529.19	0.96	2010–04
2.87	0.00	0.00	0.00	0.25	0.00	0.67	0.16	31171.74	2664.20	1285.90	0.96	2010–05
0.46	0.00	0.00	0.00	0.00	0.00	0.89	0.03	1170.65	1795.30	1001.24	0.98	2010–06
0.00	0.00	0.00	0.34	0.00	0.00	0.46	0.20	0.00	3460.91	1129.96	0.99	2010–07
0.00	0.00	0.00	0.29	0.00	0.03	0.69	0.15	9088.26	4715.84	3723.38	0.91	2010–08
0.00	0.00	0.00	0.00	15.97	0.00	0.23	0.10	2216.07	2164.65	1630.03	0.93	2010–09
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2010–10
0.00	0.00	0.00	0.59	109.59	0.00	0.00	0.02	3286.17	1594.65	0.00	1.00	2010–11
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2010–12

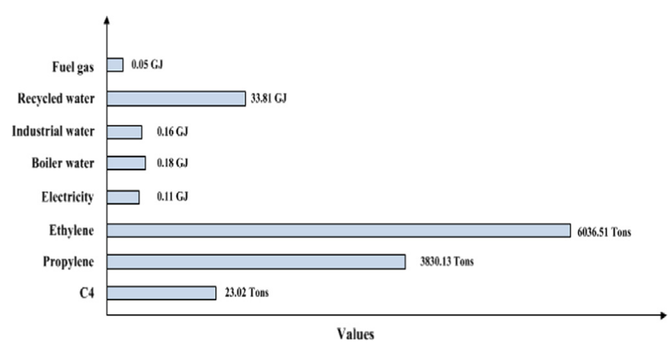

Fig. 8. The slack variables of another plant in July, 2009.

The first setB_j, the reachable set S_i and their intersection $S_i \cap B_j$in the first level can be obtained by the reachability matrix$R$. The ISM model is shown in Table 4.

In Table 4, the elements that affect the ethylene plant energy consumption in the first level can be got, and the entries that are contained in the first level of reachability matrix R are removed, then the elements at each level can be built, and the ISM model will be built in the following:

It can be seen from Fig. 5 that he main significant factors that affect the energy efficiency of I class are PONA, heavy oil, ultra-high pressure steam, recycled water, industrial water, boiler water, electricity, etc. The second layer factors, such as light oil, high pressure steam and low pressure steam, are affected by the first-level element of the crude oil, its water and electricity. And they not only play a linkage role in the energy efficiency of an ethylene plant, but also have an impact on the medium-pressure steam.

The main factors of the first lever in ISM sever as inputs of the DEA, and the production of the main products ethylene, propylene and C_4 are taken as outputs of the DEA. We can obtain the ethylene production efficiency values and the slack variables of each plant in the latest 10 years were obtained by Eq. (4) in Fig. 6.

Fig. 6 shows that, the efficiency values of this plant in some month are 1, such as from October 2001 to July 2002 and from April 2004 to April 2005, etc., which indicate that the production statuses of these months are effective. Before 2006, the energy efficiency conation of the plant is basically stable. However, from 2006, the efficiency values fluctuate greatly, which show that the plant has changed the technology and the scale, which leads to the input and output changed. For these months which the efficiency values are less than 1, the improvement direction of various months can be obtained by the input and output slack variables. The slack variables of the plant from 2009 to 2010 are shown in Table 5.

From Table 5, the DEA efficiency value of the plant in February 2009 is 0.97. If its ethylene production inputs reduce 0.49 GJ Ultra-high pressure steam, 14.64 GJ recycled water, 0.01 GJ industrial water and 0.05 GJ electricity per ton of ethylene, and outputs increase 969.65 t propylene, then the DEA efficiency value of this months can achieve the effective level. Similarly, if the ethylene production inputs reduce 15.97 GJ recycled water 0.23 GJ boiler water and 0.1 GJ electricity per ton of ethylene, and outputs increase 2216.07 t ethylene, 2164.65 t propylene and 1630.03 t C4, then DEA efficiency value of September 2010 can also achieve the effective level. The other ineffective ethylene production plant can also be got the similar analysis.

Similarly, the ethylene production efficiency values of another plant in the latest 10 years are obtained in Fig. 7 as following.

It can be seen from Fig. 7 that the efficiency values of the plant in most months are 1, which indicate that the production statuses of these months are effective. Meanwhile, in addition to January 2001 and August 2009, the efficiency values of the plant in other months are more than 0.95, which show that the energy efficiency conation of the plant is basically stable. Moreover, the improvement direction of various inefficiency months can be obtained by the input and output slack variables as same as the Table 4. As shown in Fig. 8, the DEA efficiency value of the plant in July 2009 is 0.86. If its ethylene production inputs reduce 0.05 GJ fuel gas, 33.81 GJ recycled water, 0.16 GJ industrial water 0.18 GJ industrial water, and 0.11 GJ electricity per ton of ethylene, and outputs increase 6036.51 t ethylene, 3830.13 t propylene and 23.02 t C4, then DEA efficiency value of this months can achieve the effective level.

If Comparing with the efficiency values of the plant in Fig. 6, we can obtain that production statuses of the plant in Fig. 7 is better than the plant in Fig. 6, which show that the plant in Fig. 7 has keep the production scale, and the input- output ratio remain normal. If the plant in Fig. 6 will change the technology or the scale in future, it can study the experience and technology of the plant in Fig. 7.

By analyzing energy efficiency of this technology, we can obtain the main factors and basic reasons that affect the energy consumption of the ethylene production system by the ISM method. Meanwhile, the benchmark of the effective production status and the improvement directions of the ineffective of the ethylene plants are obtained by the DEA. Moreover, the integrating evaluation method can be application in other technologies of the ethylene production systems.

7. Conclusion

The paper proposes the energy efficiency analysis framework based on the DEA model with the linear programming integrated the ISM method. The ISM based on the partial correlation coefficient method can overcome the subjectivity shortcoming. Meanwhile, this proposed method is able to overcome the disadvantage of massive inputs and outputs in the DEA model. And the analysis framework combined the DEA and the ISM is verified by using the real energy data of the ethylene production system to analyze the relationship of energy efficiency month data between different production plants in the same technology. The main factors that affect the energy consumption of the ethylene product systems and the energy efficiency in ethylene production plants could be objectively analyzed based on the ISM. Moreover, the DEA model also introduces slack variables to offer the opportunity and direction for energy saving in ethylene production, helping to improve saving measures for the ethylene plants, so the energy efficiency conditions of different plants could be described. The combined method has been proved to be able to describe energy efficiency trends of different production plants objectively, with effectiveness and usability. Furthermore, this method is also applicable to energy efficiency evaluation of other systems in the petrochemical process.

In our future studies, we will take the effect of economic development, capital, human resource and environmental planning on the energy consumption of ethylene plants into account. Moreover, we will investigate and integrate other methods, such as fuzzy analytic hierarchy process, artificial neural network, DEA with variable return to scale (VRS), DEA cross model, etc., to analyze the scale efficiency, input–output energy measuring of ethylene product process, and to compare with the current work. Furthermore, we look forward to seeing future research extensions in various environmental and energy issues of ethylene industries in the petrochemical field, as discussed in this study.

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