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Energy efficiency analysis method based on fuzzy DEA cross-model for ethylene production systems in chemical industry

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ABSTRACT

DEA (data envelopment analysis) has been widely used for the efficiency analysis of industrial production process. However, the conventional DEA model is difficult to analyze the pros and cons of the multi DMUs (decision-making units). The DEACM (DEA cross-model) can distinguish the pros and cons of the effective DMUs, but it is unable to take the effect of the uncertainty data into account. This paper proposes an efficiency analysis method based on FDEACM (fuzzy DEA cross-model) with Fuzzy Data. The proposed method has better objectivity and resolving power for the decision-making. First we obtain the minimum, the median and the maximum values of the multi-criteria ethylene energy consumption data by the data fuzzification. On the basis of the multi-criteria fuzzy data, the benchmark of the effective production situations and the improvement directions of the ineffective of the ethylene plants under different production data configurations are obtained by the FDEACM. The experimental result shows that the proposed method can improve the ethylene production conditions and guide the efficiency of energy utilization during ethylene production process.

1. Introduction

The development of chemical industry has become a main sign of industrialization of a country. The ethylene industry is one of the most important parts of the chemical industry. In 2012, 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 [1]. The ethylene production capacity of China National Petroleum Corporation was 5110 kt/a, and the fuel plus power consumption was 628.6 kg per ton of ethylene produced in 2012 [2]. Energy consumption costs of ethylene plants took up more than 50% of operating costs [3]. The energy efficiency of China ethylene industry is significantly lower than that of the advanced countries, so the study of energy efficiency analysis of ethylene plants is beneficial for both the environmental and the continued sustainable development of the Chinese economy.

Currently, the mean method and optimal index method to analyze energy efficiency are commonly used by enterprises [4]. However, the energy saving knowledge does not taken into account, so the two methods cannot give the energy efficiency value benchmarking of optimal factors and indices to guide the analysis of the actual energy efficiency state. Geng et al. proposed an energy efficiency analysis method of ethylene plants based on data fusion with better performance, but the method did not take the role of influential factors on energy consumption indicators into consideration [5,6]. These methods based on the DEA (data envelopment analysis) model and AHP (analytic hierarchy process) have been applied to the efficiency analysis of logistics, agriculture and other industries [7,8]. However, ethylene monthly data are the statistical data, which has the characteristics of multi-dimension, noise and uncertainty, resulting in the larger data error. It is difficult to evaluate accurately the energy efficiency production situation of each plant based on energy efficiency monthly data [9,10]. Frequently, the decision-making problems of ethylene plants are ill defined as their objectives and parameters are not precisely known. Therefore, this paper studies the energy efficiency analysis of China ethylene plants based on FDEACM (fuzzy DEA cross-model) with fuzzy data.

The rest of this paper has been organized as follows: Section 2 presents the research status of energy efficiency with DEA and

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fuzzy set. The fuzzy numbers and its operations are provided in Section 3. Section 4 presents the details of the FDEACM with fuzzy data. The energy efficiency analysis framework and process based on FDEACM 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 FDEACM. Finally, the conclusions are given in Section 7.

2. Literature review

In 1978, the DEA method was firstly proposed by the famous operational research experts A. Charnes, W.W. Cooper and E. Rhodes. They used the DEA to make ‘production apartment’, which had multiple inputs and multiple outputs, both ‘sizeable effective’ and ‘technological effective’. Meanwhile, the highly relevant of input–output indicators would not affect the stability and reliability of the DEA [11]. Cook and Seiford provided some of the important areas of research about the DEA that have emerged over the past three decades [12]. The application of DEA turned out to be much satisfactory and effective [13], especially in the petrochemical industry. Sueyoshi and Yang et al. 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 [14–16]. Erturk and Turut-Aşık analyzed the performance of 38 Turkish natural gas distribution companies by using the DEA method to detect the important criteria affecting the efficient levels and find the common characteristics of the most inefficient firms, [17]. Liu et al. evaluate the power-generation efficiency of major thermal power plants in Taiwan during 2004–2006 by using the DEA approach [18]. Sueyoshi and Riccardi et al. incorporated the desirable and undesirable outputs for the performance evaluation of Japanese fossil fuel power generation and the world cement industry [19,20].

One limitation of the conventional DEA models is that they can only handle crisp input and output data. However, the observed values of the input and output data in real-world problems are sometimes imprecise or vague. Imprecise or vague data may be the result of unquantifiable, incomplete and nonobtainable information. Imprecise or vague data is often expressed with bounded intervals, ordinal (rank order) data or fuzzy numbers. In recent years, many researchers have formulated FDEA (fuzzy DEA) models to deal with situations where some of the input and output data are imprecise or vague. The aim of this paper is to study the fuzzy methods for dealing with the imprecise and ambiguous data in DEA.

Fuzzy set algebra developed by Zadeh is the formal body of theory that allows the treatment of imprecise and vague estimates in uncertain environments [21]. Meanwhile, the application of fuzzy set theory in real world decision-making problems has given very interesting results. Techniques of data fusion are integrated from a wide variety of disciplines including signal processing, pattern recognition, statistical estimation, artificial intelligence, fault diagnosis, control theory and engineering, etc [22–26]. Coppi et al. proposed an FKM (fuzzy *k*-means clustering) model for LR fuzzy data and a PKM (possibilistic *k*-means clustering) model for the same type of data. The results of two applications in car and student fuzzy data confirm the validity of both models [27]. Hullermeier briefly reviews some typical applications and highlights potential contributions that fuzzy set theory can make to machine learning, data mining, and related fields [28]. Chen et al. extend a fuzzy mining approach for handling time-series data to find linguistic association rules, and made some experiments to show the performance of the proposed mining algorithm [29]. Dubchak et al. proposed a fuzzy data processing method based on Mamdani's fuzzy inference method to reduce the number of operations during fuzzy data processing and improves its performance [30].

Since the original study by Sengupta there has been a continuous interest and increased development in FDEA literature [31,32]. Zhang et al. proposed a macro model and a micro model for the efficiency evaluation of data warehouses by applying DEA and FDEA models [33]. Chiang and Che proposed a new weight-restricted FDEA methodology for ranking new product development projects at an electronic company in Taiwan [34]. Kao and Lin explored a method for measuring the fuzzy efficiency of parallel production systems which involved a number of independent processes where the input/output data are fuzzy numbers [35]. Chen et al. incorporated FDEA technique into the SBM model to evaluate risk characteristics and estimate efficiencies in the banking sector [36]. Ghapanchi et al. employed FDEA to evaluate the performance of ERP (enterprise resource planning) packages [37]. Azadeh et al. used a triangular form of fuzzy inputs and outputs instead of the crisp data and proposed an FDEA model for calculating the efficient scores of the DMUs under uncertainty with application to the power generation sector [38]. Azadeh et al. explored an integrated approach for performance evaluation of health safety environment divisions, involving DEA and FDEA, to lessen the human error and the data imprecision [39]. Moreover, Azadeh et al. proposed an adaptive-network-based fuzzy inference system-FDEA algorithm for improving the long-term natural gas consumption forecasting and analysis [40].

The quantities of input and output indicators and the number of samples had an influence on the results of DEA and FDEA analysis [41,42]. The DEA model can lead to the situation that more than one-third of efficiency values are set to 1, so it means efficiency discrimination is poor. It also cannot obtain the sort of effective DMUs (decision-making units). Thus the DEA model can only distinguish the effective and ineffective units when analyzing enterprise production plant efficiency, but cannot give further evaluation and comparison of multi-effective DMUs. Moreover, in order to get the maximum efficiency evaluation index of each DMU, the weight allocation of input and output indicators is usually unreasonable [12]. Therefore the DEACM (DEA cross-model) is applied to analyze the energy efficiency status of the chemical industry.

In 1986, Sexton proposed the DEACM [43]. Chen used the DEA framework to compare cross-efficiency scores and the technical efficiency of the electricity distribution sector in Taiwan [44]. Wang and Chin introduced several kinds of the DEACM and its application [45]. Lu et al. study the DEACM to provide a theoretical basis for reference in grasping the actual level of thermal power units and charting the direction of improvement [46]. Yu et al. used the cross-efficiency DEA approach to identify the most efficient scenario and analyze the efficiency of each information-sharing scenario in supply chains [47]. The DEACM can distinguish the pros and cons of the effective DMUs, but it is unable to take the effect of the uncertainty data into account.

Considering the characteristics of the fuzzy set and the DEACM, this paper proposes an FDEACM based on fuzzy data. Firstly the monthly data are blurred to obtain the minimum, average and maximum values of ethylene production energy efficiency data. On the basis of the multi-criteria fuzzy fusion data, the corresponding energy efficiency situations of the ethylene plant under different production data configurations are obtained by the FDEACM. This approach is used to evaluate and analyze performance of petroleum chemical plants 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.

3. Fuzzy numbers and its operations

3.1. Triangular fuzzy number

Although there are many shapes of fuzzy numbers, triangular fuzzy numbers and trapezoidal fuzzy numbers are usually employed to capture the vagueness of the parameters related to the selection of the alternatives. In this study, we use TFNs (triangular fuzzy numbers) to prioritize competitiveness to analyze the energy efficiencies of ethylene product process.

A fuzzy number $A = (a,b,c)$ $(a \le b \le c)$ on R to be a TFN if its membership function $\mu_A(x)$: $R \to [0,1]$ is equal to following Eq. (1):

$$\mu_A(x) = \begin{cases} (x-a)/(m-b), & a \le x \le b \\ (c-x)/(c-b), & b \le x \le c \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

The following definition describes the membership function of fuzzy numbers and the operations on them.

Let $A_1 = (a_1 \quad b_1 \quad c_1)$ $(a_1 \le b_1 \le c_1)$ and $A_2 = (a_2 \quad b_2 \quad c_2)$ $(a_2 \le b_2 \le c_2)$ be any two triangular fuzzy numbers. The operations laws are obtained in literature [48].

3.2. Satisfaction with fuzzy numbers

Suppose that there are two triangular fuzzy numbers $A_1 = (a_1 \quad b_1 \quad c_1)$ $(a_1 \le b_1 \le c_1)$ and $A_2 = (a_2 \quad b_2 \quad c_2)$ $(a_2 \le b_2 \le c_2)$.

Definition 1. The intersections of the membership function of A_1 and A_2 are calculated as follows:

$$\alpha_* = \begin{cases} 1 - \dfrac{b_2 - b_1}{c_1 + a_2}, & 0 \le b_2 - b_1 \le c_1 + a_2 \\ 1 - \dfrac{b_1 - b_2}{a_1 + c_2}, & 0 \le b_1 - b_2 \le a_1 + c_2 \\ 0, & \text{others} \end{cases} \tag{2}$$

If there is an intersection in two triangular fuzzy numbers, Eq. (2) could be able to reflect the relationship between two triangular fuzzy numbers which have the only one point of intersection, and it is also the center points of two triangular fuzzy numbers.

By using the membership values which constructed at the intersection of the two triangular fuzzy number, the satisfaction formula can be used to compare the fuzzy numbers.

Definition 2. The satisfaction P of $A_1 \le A_2$ is defined as [49]:

$$P_n(A_1 \le A_2) = \begin{cases} 1 - \alpha_*^n \dfrac{c_1 + a_2}{a_1 + c_1 + a_2 + c_2}, & A_1 \le A_2 \\ \alpha_*^n \dfrac{c_2 + a_1}{a_1 + c_1 + a_2 + c_2}, & A_1 \ge A_2 \end{cases} \tag{3}$$

For any two triangular fuzzy numbers A_1 and A_2 have the following properties:

(1) $0 < P_n(A_1 \le A_2) \le 1$
(2) When $\tilde{A} = \tilde{B}$, then $P_n(A_1 \le A_2) = 1 - ((c_1 + a_2)/(c_1 + a_1 + c_2 + a_2))$
(3) When $b_1 + c_1 \le b_2 - a_2$, $P_n(A_1 \le A_2) = 1$
(4) $P_n(A_1 \le A_2) \le 1 - P_n(A_2 \le A_1)$

In which, n is a constant, and the increase of n can more effectively distinguish between triangular fuzzy numbers. In practical applications, it can be generally considered as $n = 3$. The larger value of n is not the better case, you should take the real problems into account and get a reasonable amount of computation to select.

4. The method of FDEACM with data fuzzification

4.1. Data fuzzification

Assume select a set of n data $x_1, x_2, x_3, \ldots, x_n$.

Select a piece of data at intervals of m data $(0 < m \le n)$, that is $x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+m-1}$.

The minimum L, the max H, and the average value are calculated to get the fuzzy mean P. Then we can obtain the following equation:

$$L = \min\{x_i, x_{i+1}, \ldots, x_{i+m-1}\}, \quad H = \max\{x_i, x_{i+1}, \ldots, x_{i+m-1}\}, \quad P = \frac{(x_i + x_{i+1} + \cdots + x_{i+m-1})}{m} \tag{4}$$

The data L' and H' are obtained by the following Eq. (5):

$$L' = \begin{cases} P - 2(P-L), P \ge 2(P-L) \\ 0, P \le 2(P-L) \end{cases}, \quad H' = P + 2(H-P) \tag{5}$$

According to the definition, these m data's Gaussian membership function of triangular fuzzy numbers can be calculated as:

$$\mu_S = \begin{cases} 1, & x \le L' \\ e^{\frac{1}{2}\left(\frac{x-L'}{\frac{H'-L'}{\sigma}}\right)^2}, & L' < x < \dfrac{L'+H'}{2} \\ 0, & x \ge \dfrac{L'+H'}{2} \end{cases} \tag{6}$$

$$\mu_M = \begin{cases} 0, & x \le L' \\ e^{-\frac{1}{2}\left(\frac{x-\frac{L'+H'}{2}}{\frac{H'-L'}{\sigma}}\right)^2}, & L' < x < H' \\ 0, & x \ge H' \end{cases} \tag{7}$$

$$\mu_L = \begin{cases} 0, & x \le \dfrac{L'+H'}{2} \\ e^{-\frac{1}{2}\left(\frac{x-H'}{\frac{H'-L'}{\sigma}}\right)^2}, & \dfrac{L'+H'}{2} < x < H' \\ 0, & x \ge H' \end{cases} \tag{8}$$

The selected m data, $x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+m-1}$, are substituted into μ_S, μ_M and μ_L, according to x_S, x_M and x_L corresponding to the maximum of μ_S, μ_M and μ_L, and then it can obtain a set of triangular fuzzy number (x_S, x_M, x_L)

So it can get k $(k = n/m)$ set of triangular fuzzy numbers

$$(x_{S_1}, x_{M_1}, x_{L_1}), (x_{S_2}, x_{M_2}, x_{L_2}) \ldots (x_{S_k}, x_{M_k}, x_{L_k})$$

where $k = n/m$.

4.2. DEACM (DEA cross-model)

The DEACM is a new method by taking DEA as a sorting tool of DMUs. Because the unreasonable weight allocation of inputs and outputs is avoided, each DMU can be evaluated effectively [43].

Assume that there are n plants or units (namely decision-making units, abbreviated DMU), each DMU has m inputs and s outputs. x_{ji} and y_{ri} denotes the jth input and the rth output of DMU$_i$ ($i = 1,2,\ldots,n$; $j = 1,2,\ldots,m$; $r = 1,2,\ldots,s$), respectively. DMU$_i$ is evaluated by Eq. (9) with the CCR (Charnes, Cooper and Rhodes) model of the DEA.

$$\begin{cases} \max \dfrac{y_i^{\mathrm{T}} u}{x_i^{\mathrm{T}} v} = E_{ii} \\ \dfrac{y_l^{\mathrm{T}} u}{x_l^{\mathrm{T}} v} \le 1, \quad l = 1,2,\ldots,n \\ u \ge 0, \ \ v \ge 0, \ \ u \ne 0, \ \ v \ne 0 \end{cases} \tag{9}$$

wherein $x_i = (x_{1i}, x_{2i}, \ldots, x_{mi})^{\mathrm{T}} > 0$, $y_i = (y_{1i}, y_{2i}, \ldots, y_{si})^{\mathrm{T}} > 0$, $v = (v_1, v_2, \ldots, v_m)^{\mathrm{T}}$ and $u = (u_1, u_2, \ldots, u_s)^{\mathrm{T}}$ denote weight coefficients of m inputs and s outputs, respectively. The equivalent LP (linear programming) used the Charnes–Cooper transform to transform the CCR model.

$$\begin{cases} \max y_i^{\mathrm{T}} u = E_{ii}, \\ y_l^{\mathrm{T}} u - x_l^{\mathrm{T}} v \le 0, \ \ l = 1,2,\ldots,n, \\ x_i^{\mathrm{T}} v = 1, \\ u \ge 0, \ \ v \ge 0 \end{cases} \tag{10}$$

Assume that Eq. (10) have the optimal weight u_i^* and v_i^* , which denoted $w_i^* = (v_i^*, u_i^*)^{\mathrm{T}}$, the optimal values are $E_{ii} = y_i^{\mathrm{T}} \mu_i^*$ denoting the efficiency values of DMU$_j$, i.e., self-evaluation value [43]. In the DEA, if $E_{ii} = 1$, then the DMU$_i$ is considered effective, or the DMU$_i$ is considered ineffective.

The following LP is solved by using the self-evaluation value E_{ii} of DMU$_i$ in Eq. (10) [50,51]:

$$\begin{cases} \min y_k^{\mathrm{T}} u \\ y_l^{\mathrm{T}} u - x_l^{\mathrm{T}} v \le 0, \quad l = 1,2,\ldots,n, \\ y_i^{\mathrm{T}} u = E_{ii} x_i^{\mathrm{T}} v, \ \ x_k^{\mathrm{T}} v = 1, \\ u \ge 0, \ \ v \ge 0 \end{cases} \tag{11}$$

wherein $i \in \{1,2,\ldots,n\}$ and $k \in \{1,2,\ldots,n\}$.

Then the cross-evaluation value can be calculated by the optimal weight u_{ik}^* and v_{ik}^* of Eq. (11).

$$E_{ik} = \frac{y_k^{\mathrm{T}} u_{ik}^*}{x_k^{\mathrm{T}} v_{ik}^*} \tag{12}$$

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

$$E = \begin{pmatrix} E_{11} & E_{12} & \ldots & E_{1n} \\ E_{21} & E_{22} & \ldots & E_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ E_{n1} & E_{n2} & \ldots & E_{nn} \end{pmatrix} \tag{13}$$

wherein, the main diagonal element E_{ii} and the non-diagonal element E_{ik} ($i \ne k$) denote the self-evaluation value and the cross-evaluation value, respectively. The ith row of E denotes the evaluation values of each DMU. The lower these values, the worse DMU$_i$. Therefore, the mean values of the ith row of E

$$e_i = \frac{1}{n} \sum_{k=1}^{n} E_{ki} \tag{14}$$

is used as a criterion to evaluate DMU$_i$. The total evaluation of each DMU for DMU$_i$ is the e_i. The higher e_i, the better DMU$_i$.

4.3. FDEACM (fuzzy DEA cross-model)

The actual production shows that the input is fewer, and the output is larger, and then the energy efficiency is the higher. Assume that the fuzzy amount of inputs and outputs are$(x_i)^t = ((x_i)^S,(x_i)^M,(x_i)^L)$ and$(y_i)^t = ((y_i)^L,(y_i)^M,(y_i)^S)$ ($i = 1,2,\ldots,n$; $t = S,M,L$; $S \le M \le L$) respectively. When the fuzzy DMU produces with the minimum input amount $(x_i)^S$ and the maximum output amount $(y_i)^L$, it is the well production practice point. When the fuzzy DMU produces with the maximum input amount $(x_i)^L$ and the minimum output amount $(y_i)^S$, it is the bad production configuration. When the fuzzy DMU produces with the mean input amount $(x_i)^M$ and the mean output amount $(y_i)^M$, it is daily operation production. We use the equation form of the dual model of Eq. (9) (with fuzzy data), i.e., input-oriented FDEA model:

$$\begin{cases} \max y_{it}^{\mathrm{T}} u = E_{iit}, \\ y_{lt}^{\mathrm{T}} u - x_{lt}^{\mathrm{T}} v \le 0, \quad l = 1,2,\ldots,n, \\ x_{it}^{\mathrm{T}} v = 1, \\ u \ge 0, \ \ v \ge 0 \end{cases} \tag{15}$$

In FDEA, if $E_{iit} = 1$, then DMU$_i$ is considered effective, and if $E_{iit} < 1$, then DMU$_i$ is considered ineffective.

By using the fuzzy self-evaluation value E_{iit} of DMU$_i$ in Eq. (15), $i \in \{1,2,\ldots,n\}$ and $k \in \{1,2,\ldots,n\}$ are given to solve the following LP:

$$\begin{cases} \min y_{kst}^{\mathrm{T}} u \\ y_{lst}^{\mathrm{T}} u - x_{lst}^{\mathrm{T}} v \le 0, \quad l = 1,2,\ldots,n, \\ y_{ist}^{\mathrm{T}} u = E_{iit} x_{ist}^{\mathrm{T}} v, \ \ x_{kst}^{\mathrm{T}} v = 1, \\ u \ge 0, \ \ v \ge 0, \ \ t = S,M,L; \ S \le M \le L \end{cases} \tag{16}$$

Then the fuzzy cross-evaluation value can be calculated by the optimal solution u_{ikt}^* and v_{ikt}^* of Eq. (21):

$$E_{ikt} = \frac{y_{kt}^{\mathrm{T}} u_{ikt}^*}{x_{kt}^{\mathrm{T}} v_{ikt}^*} \tag{17}$$

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

$$E_t = \left(\begin{pmatrix} E_{11S} & E_{12S} & \ldots & E_{1nS} \\ E_{21S} & E_{22S} & \ldots & E_{2nS} \\ \ldots & \ldots & \ldots & \ldots \\ E_{n1S} & E_{n2S} & \ldots & E_{nnS} \end{pmatrix}, \begin{pmatrix} E_{11M} & E_{12M} & \ldots & E_{1nM} \\ E_{21M} & E_{22M} & \ldots & E_{2nM} \\ \ldots & \ldots & \ldots & \ldots \\ E_{n1M} & E_{n2M} & \ldots & E_{nnM} \end{pmatrix}, \begin{pmatrix} E_{11L} & E_{12L} & \ldots & E_{1nL} \\ E_{21L} & E_{22L} & \ldots & E_{2nL} \\ \ldots & \ldots & \ldots & \ldots \\ E_{n1L} & E_{n2L} & \ldots & E_{nnL} \end{pmatrix} \right) \tag{18}$$

Table 1
The features of different methods introduced in this paper.

Method	Characteristics
DEACM	① More objective, weights distributing better ② Not considering the imprecise or vague data in the real-world problems
FDEA	① More objective ② Decision-making units having restrictions
DEA	① Objective, Simple and convenient ② Decision-making units having restrictions
DEA–AHP	① Objective, Avoiding restrictions of multi-input and multi-output and decision-making units ② Not considering the imprecise or vague data in the real-world problems
FDEACM	① More objective, weights distributing better ② Avoiding restrictions of multi-input and multi-output and decision-making units

In which main diagonal element $E_{iit}\,(t = S,M,L)$ and non-diagonal element $E_{ikt}\,(k \neq i)$ denote the fuzzy self-evaluation value and fuzzy cross-evaluation value, respectively. The ith row of E denotes the evaluation values of each DMU for DMU$_i$. The higher these values, the better DMU$_i$. Thus, the mean value of the ith row of E

$$e_t = \left(\frac{1}{n}\sum_{k=1}^{n} E_{kiS}, \frac{1}{n}\sum_{k=1}^{n} E_{kiM}, \frac{1}{n}\sum_{k=1}^{n} E_{kiL}\right) \tag{19}$$

is used as a criterion to measure DMU$_i$. e_{it} can be seen as the total evaluation of each DMU for DMU$_i$. The higher e_{it}, the better DMU$_i$.

The proposed FDEACM method is relatively objective to identify the differences of criteria among alternatives, and it can trade-off the subjective marks of experts' opinions. Table 1 shows the features of different methods introduced in this paper.

It is apparent from Table 1 that the proposed FDEACM is more accurate and efficient than others. It has good objectivity and resolution.

5. An energy efficiency analysis framework and process based on FDEACM

There are about seven common process technologies in Chinese ethylene industries [48]. In this paper, we take the Lummus order separation technology as an example to illustrate the effectiveness of the proposed method.

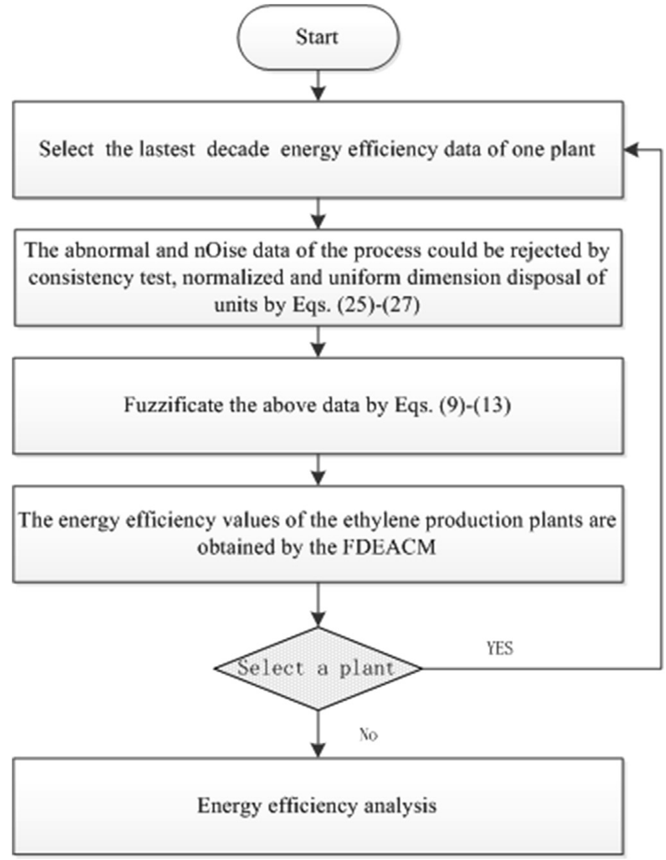

Fig. 2. The energy efficiency analysis procedure of the ethylene production plants based on the FDEACM.

The ethylene production can be divided into the cracking and the separation. When a cracking furnace is running, a large number of fuels are needed to provide heat to the tube cracking reactions, and a TLE (transfer line exchanger) produces a great number of steams by recovering the waste heat. In order to make the raw

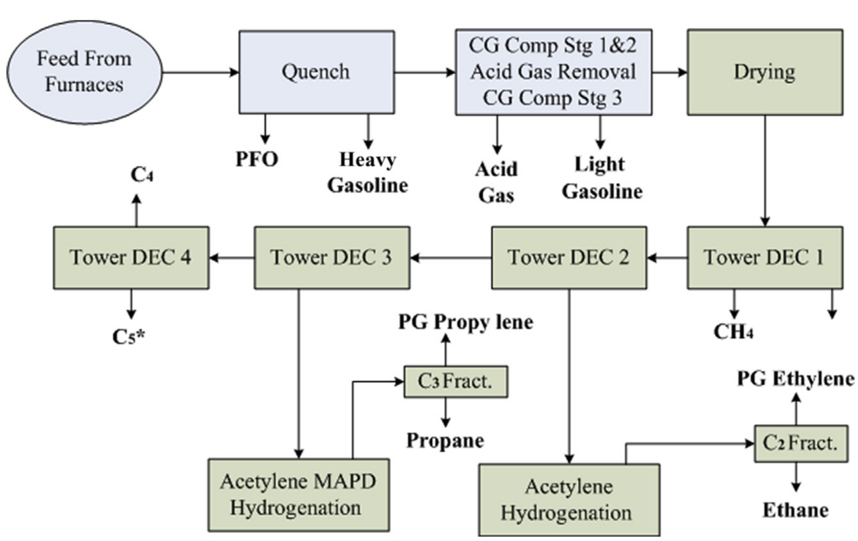

Fig. 1. A typical framework of a sequential separation process.

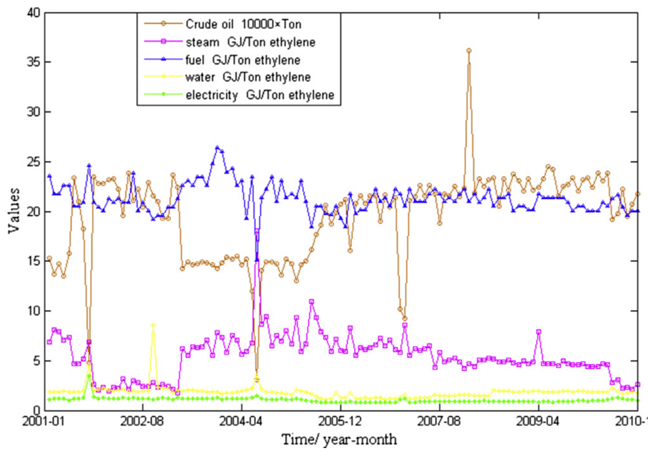

Fig. 3. The required fuels, steams, water and electricity of one ethylene plant from 2001 to 2010.

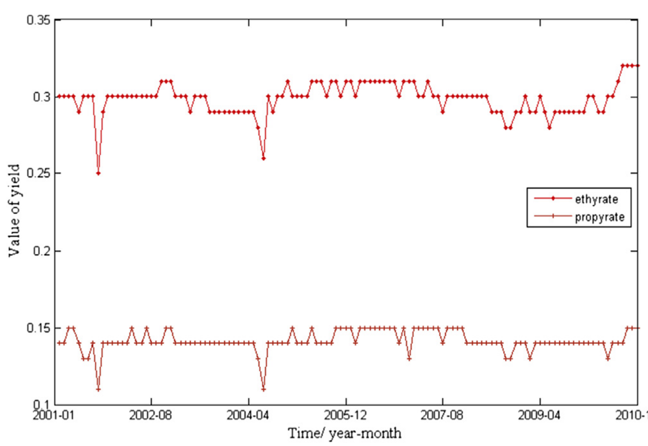

Fig. 4. The monthly yields of ethylene and propylene of one ethylene plant from 2001 to 2010.

material hydrocarbon finish the optimal cleavage reactions in a short time and reduce coke, steam should be injected when the hydrocarbon is fed into the cracking furnace.

The separation section mainly contains 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 framework of the sequential separation process is shown in Fig. 1.

5.1. Energy boundary of ethylene product system

In ethylene industries, different ethylene product plants may be quite different in division of energy utilization boundary. In order to make a unanimous criterion of computing energy efficiency objectively, we refer to the ethylene industrial standards (DB37/751-2007) and national standards for energy consumption (GB/T2589-2008) in China [52,53]. The energy utilization boundary of ethylene product system is described in lecture [48].

The main energy types are included in the ethylene utilization boundary as follows: the water including industrial water, recycle water and boiler water; the power (electricity); steams including low pressure steam, middle pressure steam, high and super-high pressure steam; fuels including light oil, heavy oil and fuel gas; N2 and compressing air. Because of the lowest consumption of N2 and compressing air among energy types, they were not computed considering energy efficiencies of ethylene product process. According to the statistics, the energy consumption fees are up to more than 50% of total cost for ethylene product process.

In ethylene production process, the main ethylene crude and ethylene production are represented by the yields of ethylene and propylene. It is difficult to obtain technology, operating conditions and waste/energy losses because of difficulty to measure or confidentiality. However, considering the ethylene yield in the production process are effected by them, thereby affecting the ethylene consumption. Therefore this article introduced the affecting factors of the yield on energy consumption. And its comprehensive influence factors are replaced by the yields for the lack of data.

5.2. Data preprocessing

Ethylene production data has complex nonlinear timing relationship, and includes noise and abnormal data, etc. And dimension for variables of the timing data is generally different, which makes values of variables incomparable [9]. Meanwhile, the efficiency of the DEA is relative. The accuracy of the analysis result is easily affected by multi-input and multi-output data of DMUs and their precision. Therefore, the ethylene production data is processed by consistency test, normalized and uniform dimension disposal of units. Eq. (20) is for the long-length data, and will lead to erroneous judgment for the short-length data [8]. However, the long-length data could be processed by the Grubbs criterion [54]: if $T \geq T(n,\alpha)$, then x_i is eliminated, n denotes the number of data and α is significant level.

$$T = \frac{|V|}{S} = \frac{|x_i - \overline{x}|}{S} \tag{20}$$

where $\overline{x} = (1/N)\sum_{i=1}^{N} x_i$, $S = \sqrt{(1/N)\sum_{i=1}^{N}(x_i - \overline{x})^2}$. The value of $T(n,\alpha)$ refers to literature 48.

Based on characteristics of energy efficiency data in 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) [55].

The general transformation method is by proportion. However, the described subjects of the timing data need to be paid attention to. For the same subject, different variables make different interactions. Some of variables are positive, and others are negative [48]. The respective equations are shown in Eqs. (21) and (22).

$$x'_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \tag{21}$$

$$x'_{ij} = 1 - \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \tag{22}$$

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

5.3. The efficiency analysis process of the ethylene plants

The process of the ethylene production is considered as a multi-input and multi-output process. The abnormal and noise data made by the process could be rejected by consistency test, normalized and uniform dimension disposal of units. And then the multi-input

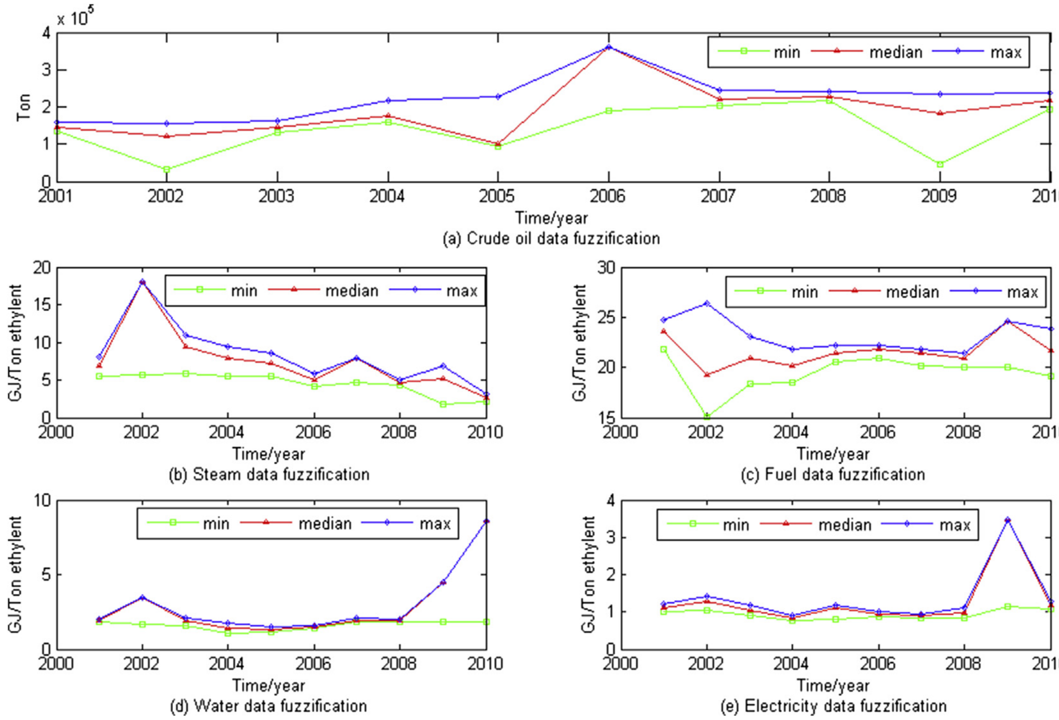

Fig. 5. The min, median and max values of the input data of one plant.

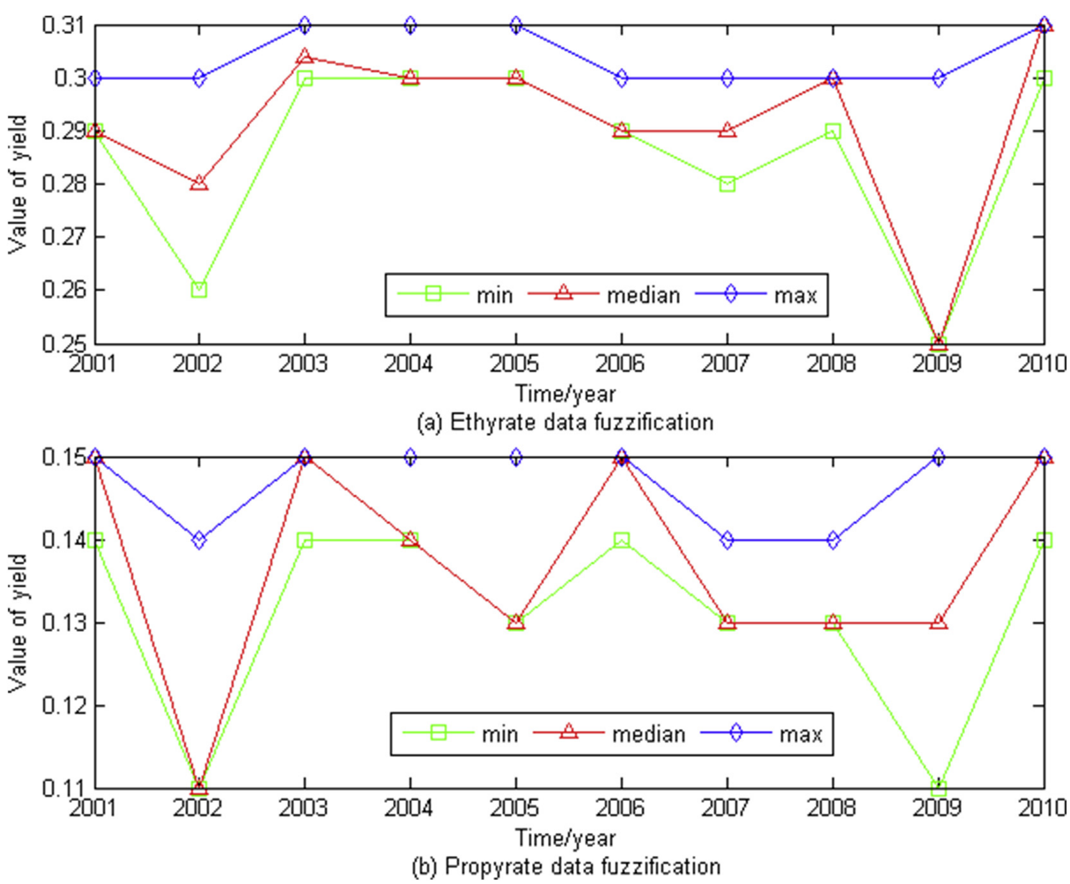

Fig. 6. The min, median and max values of the output data of one plant.

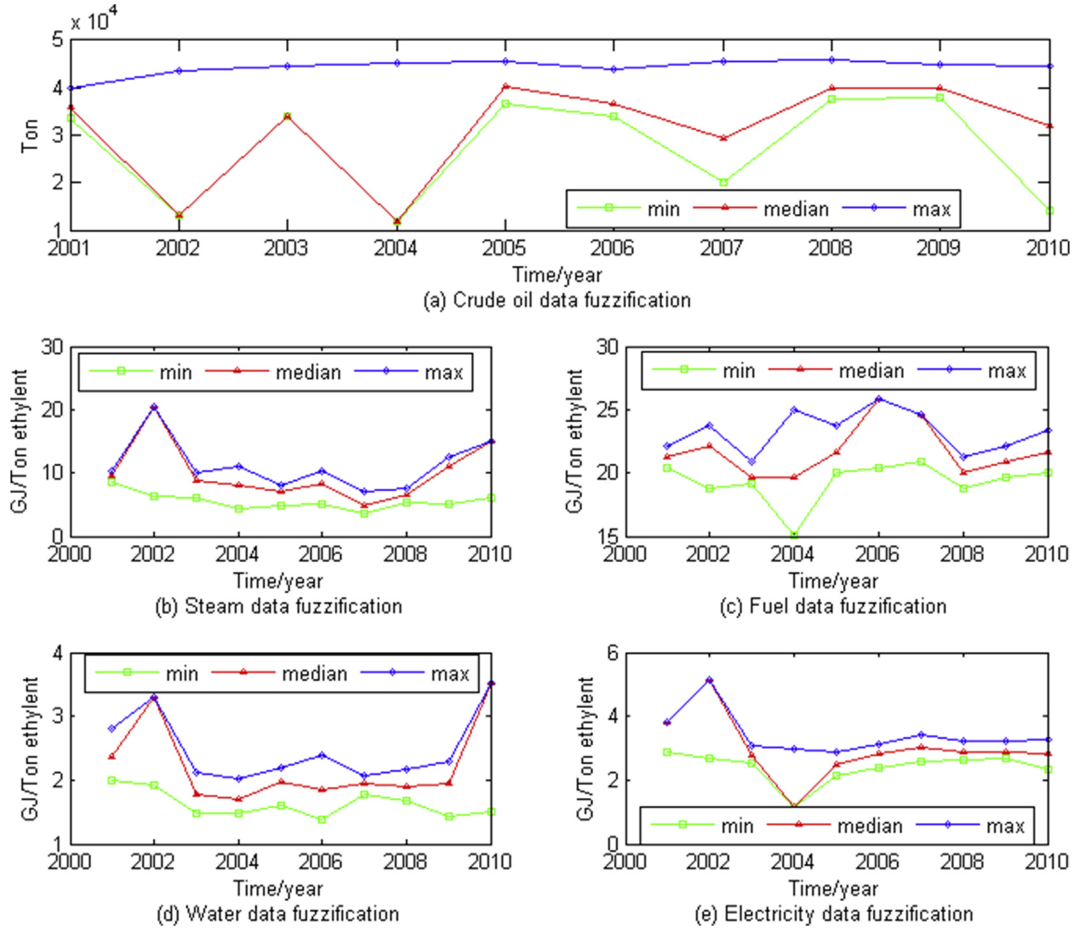

Fig. 7. The min, median and max values of the input data of another plant.

and multi-output data can be sorted more objectively and accurately. Then, the precision of energy efficiency analysis of ethylene production equipments improve significantly through data fuzzification and FDEACM analyses. These works are able to demonstrate the method of disposing feed costs under different production technologies for different plants, and the ways to improve production design and energy efficiency and how to increase production. The energy efficiency analysis procedure of ethylene production plants based on FDEACM is shown in Fig. 2.

6. Case study: the energy efficiency analysis of ethylene plants in chemical industry

In order to illustrate the efficiency of ethylene production, the order separation technology in the empirical analysis was adopted. There are nine ethylene plants in China: Qilu, Fushun, Panjin, Yangtze, Dushanzi, Central Plains, Saike ethylene, Yanshan, and Tianjin ethylene. And the monthly data of energy efficiency in the last 10 years came largely from those plants. Fig. 3 shows the plot of the whole fuels, steams, water and electricity required of one ethylene plant from 2001 to 2010, and Fig. 4 presents the monthly yields of ethylene and propylene of one ethylene plant from 2001 to 2010.

First, we make the crude, water, electricity, steam and fuel of a plant and the yields of ethylene and propylene fuzzification by Eqs. (4)–(8), and then the upper (max), the middle (median) and the lower (min) values of the yields and each working substance are shown in Figs. 5 and 6, respectively.

Similarly, the fusion data of another plant are obtained by Eqs. (4)–(8) are shown in Figs. 7 and 8.

After ethylene energy efficiency data fuzzification, combining the minimum energy consumption values under each working substance as the inputs and the maximum values of ethylene and propylene yields as the output, we can obtain the well practices production of ethylene production (well). On the contrary, it is the bad situation of the plant ethylene production (bad). The median values of the crude, water, electricity, steam and fuel and the yields of ethylene and propylene are taken as inputs and outputs of FDEACM, respectively, and then we can obtain the daily production situation (median). It can get the self-evaluation values of the well, the median and the bad productions for one plant as shown in Fig. 9.

Fig. 9 shows that the number of energy efficiency values of the plant equaling to one is greater than 1/3. However, the self-evaluation model of FDEACM, namely the FDEA model, cannot evaluate the energy efficiency of the efficient years of the plant. Fig. 10 shows the cross-evaluation efficiency values of the FDEACM.

Fig. 10 shows that when the plant inputs and outputs reach the optimal production, its energy efficiency changes little. In 2009 the energy efficiency is the highest, and the corresponding efficiency value is 0.84. Its ethylene production inputs are 47,820 ton crude oil, 1.78 GJ steam, 20.02 GJ fuel, 1.87 GJ water and 1.14 GJ electricity per ton of ethylene, and the outputs are 0.3 ethylene yield and 0.15 propylene yield. It refers to the input and output of the year for organization of future production. The daily input–output and the bad energy efficiency input–output show that, both are basically in

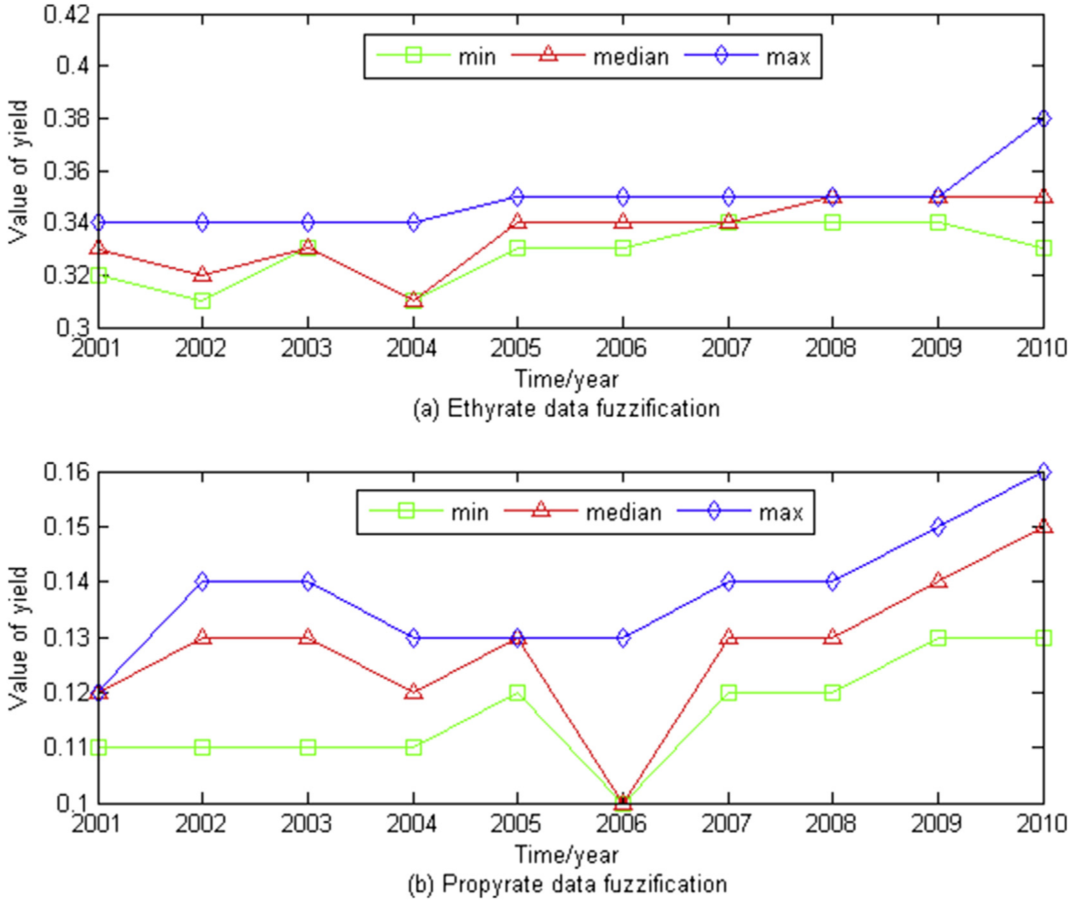

Fig. 8. The min, median and max value of the output data of the another plant.

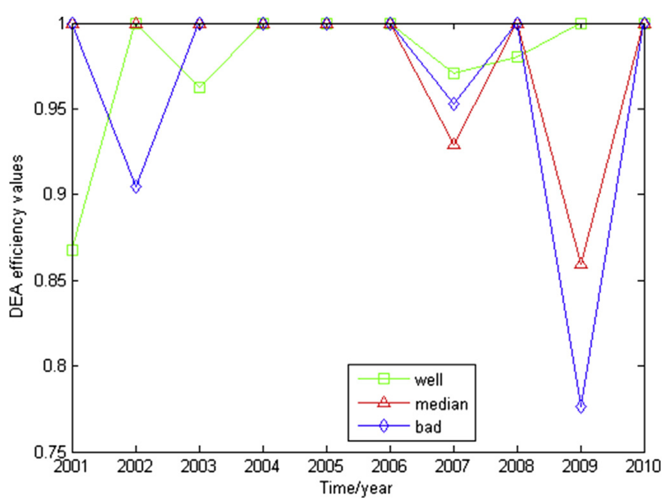

Fig. 9. The self-evaluation efficiency values of FDEACM for one plant.

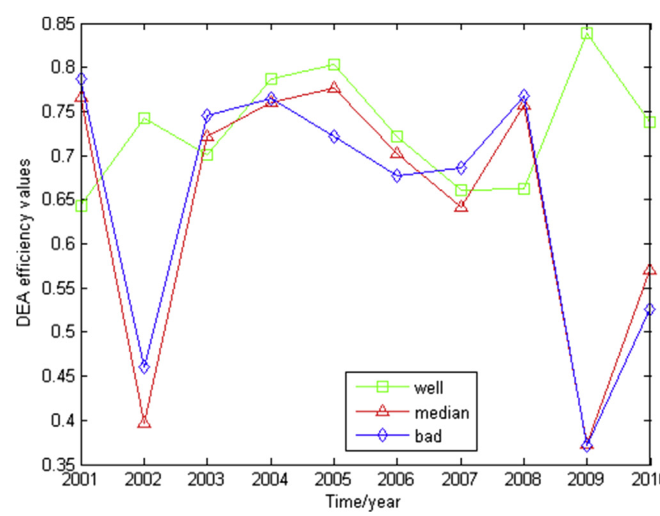

Fig. 10. The cross-evaluation efficiency values of FDEACM for one plant.

the same trend, indicating that the energy consumption of the plant is large, that is the energy efficiency is low. Especially in 2002 and 2009, the energy efficiency reached the lowest. Similarly, the efficiency value of energy efficiency input–output in 2009 is 0.37, and the ethylene production inputs are 234,596 ton crude oil, 6.85 GJ steam, 24.62 GJ fuel and 4.46 GJ water and 3.47 GJ electricity per ton of ethylene, and the outputs are 0.25 ethylene yield and 0.11 propylene yield. Therefore, if the inputs of the plant in the bad energy efficiency input–output can refer to the benchmark of the effective production situations in the well, then the output of the plant can also achieve the efficient level. The other ineffective year of this plant can also be got the similar analysis. By monthly data it is known that the plant size is larger, the crude and the energy are used more, resulting in lower energy efficiency in 2002 and 2009.

Similarly, it can obtain the cross-evaluation values of FDEACM of another plant as shown in Fig. 11.

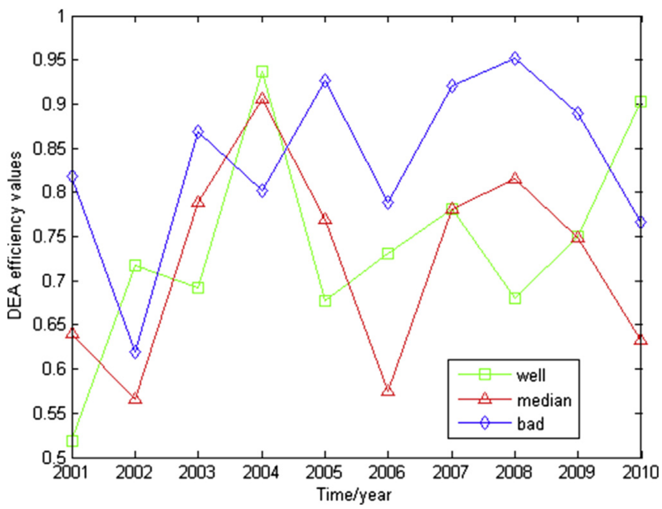

Fig. 11. The cross-evaluation efficiency values of FDEACM for another plant.

Table 2
Energy consumption fuzzy number ratios of two plants.

α_*	$P_n(A_1 \le A_2)$ $A_1 \le A_2$	$P_n(A_1 \le A_2)$ $A_1 \ge A_2$	Time
0.9130	0.6409	0.4020	2001
0.8563	0.7086	0.3365	2002
0.9532	0.5860	0.4522	2003
0.9146	0.6045	0.3695	2004
0.9961	0.5578	0.5460	2005
0.9156	0.6296	0.3973	2006
0.9042	0.6443	0.3835	2007
0.9604	0.5811	0.4671	2008
0.6660	0.8837	0.1791	2009
0.9567	0.5734	0.4491	2010

Fig. 11 shows that the energy efficiency input and output trends of the plant change greater. When inputs and outputs of this plant reach the optimal production, the energy efficiency is the highest in 2004, but the energy efficiency values of other years are relatively low. The energy efficiency productions of the median and the well have basically the same trend. By the analysis of bad inputs and bad outputs, the energy efficiency of the plant is basically stable, but its energy efficiency value is basically higher than that of the median and the well, mainly because the energy efficiency of this plant can basically achieve the optimal production. On the basis of the energy efficiency analysis and the daily production, the improvement directions of the ineffective year of this plant can be obtained like the plant in Fig. 10. Meanwhile, the plant can improve the energy efficiency by increasing the production scale.

Using the triangular fuzzy number comparison method based on Eqs. (7) and (8), we can get the intersections of the membership function α_* and the satisfaction of the plant in Fig. 10 and the plant in Fig. 11 ($P_n(A_1 \le A_2)$:$A_1 \le A_2$) in Table 2.

From $P_n(A_1 \le A_2)$ and the production median value, we can see that the overall energy consumption in Fig. 11 is smaller than that in Fig. 10, which means the ethylene production efficiency of this plant in Fig. 11 is better. The plant in Fig. 11 can increase the ethylene production, while the plant in Fig. 10 should not increase the production, but improve the technology to enhance the energy efficiency.

7. Conclusions

This paper proposed a method of FDEACM based on data fuzzification. This proposed algorithm can trade-off the subjective marks of experts' opinions. It has better objectivity and resolving power for the decision-making. Meanwhile, the proposed method is applied for analyzing the energy efficiency status of ethylene production plants. The results show that the proposed approach can obtain the rational allocation of crude, steam, fuel, water and electricity consumption and find the optimal production situation under different input and output configurations reasonably. Meanwhile, this study successfully provides information on energy consumption factors so that policy makers can utilize it to improve efficiency in the consumption of energy and guide ethylene production reasonably and improve energy efficiency efficiently.

In our further studies, we will separate input indicators into energy and non-energy inputs and incorporate desirable (good) outputs and undesirable (bad) outputs for the energy efficiency analysis of the ethylene plants in chemical industry. Moreover, we will investigate and integrate other methods, such as Fuzzy analytic hierarchy process, Fuzzy Artificial neural network, etc., to analyze the scale efficiency, input–output energy measuring of ethylene production systems, and to compare with the current work. Furthermore, the proposed method can be applied to energy efficiency analysis of other process plants.

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