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Performance analysis and optimal temperature selection of ethylene cracking furnaces: A data envelopment analysis cross-model integrated analytic hierarchy process

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ABSTRACT

Ethylene is an important raw material of industrial products, and the performance analysis of ethylene cracking furnaces in the petrochemical industry is affected mainly by the temperature. Therefore, this paper presents a performance analysis and optimal temperature selection method of ethylene cracking furnaces using the data envelopment analysis cross-model (DEACM) integrated analytic hierarchy process (AHP) (DEACM-AHP). The DEACM avoiding the unreasonable weight distribution of input-output factors can accurately identify and estimate the performance status and the optimal temperature of ethylene cracking furnaces. Meanwhile, the improved AHP based on the entropy weight can comprehensively consider the reasonable weight allocation of each input-output index and obtain the consistent fusion result of ethylene cracking furnaces with different temperatures. And then the optimal production benchmark with different temperatures is obtained based on the DEACM again. Finally, the proposed approach is applied to the performance analysis and optimal temperature selection of the SL-I type naphtha cracker model in the petrochemical field. The experimental result shows the proposed method can guide the ethylene production system to reduce energy consumption and improve energy efficiency.

1. Introduction

The industrialization of a country is mainly affected by the petrochemical productivity, especially the ethylene productivity of complex petrochemical industries. The present demand for the ethylene production is over 155 million tons per year and has been increasing [1,2]. In 2014, the ethylene production of China Petrochemical Corporation and China National Petroleum Corporation was 10420 kt/a and 4976 kt/a, respectively. However, the average fuel and power consumption was 571.39 kg per ton of ethylene and 616.7 kg per ton of ethylene, respectively [3,4]. Thus compared with the developed countries, the ethylene production efficiency of China is obviously lower. Moreover, the thermal cracking is the only available industrial process exists for the olefins production. Meanwhile, the thermal cracking furnace is the heart of the olefin production process and the main factor in both smooth running and economic of olefin plants. Therefore, the performance analysis and optimal temperature selection of ethylene cracking furnaces are beneficial for both the environment and the sustainable development of the petrochemical industry.

In order to improve the ethylene yield, Goethem et al. utilized the kinetics to optimize the reaction conditions of the steam cracking [5]. Goswami analyzed a specific kind of failure in ethylene cracking coils coated with anticaking film and pointed out the high temperature having a significant impact on the ethylene production [6]. Varzaneh et al. studied the effect of cerium and zirconium on the yield of ethylene and propylene by comparing the catalytic performance of naphtha cracking over SAPO-34 and HZSM-5 [7]. Subramanian et al. analyzed the effects of temperature on the yields of the major aliphatic and aromatic products of supercritical n-Decane pyrolysis [8]. Zhao et al. acquired an improvement in overall profit and attained significant enhancement in energy savings of the ethylene plant by analyzing energy utilization of the thermal cracking based on the multi-period mixed-integer nonlinear programming (MINLP) model [9]. Sadrameli discussed the

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main research works done on the thermal and catalytic cracking of hydrocarbons for the olefins production in the last five decades [10]. However, these mechanism models for optimizing productive process were complex and did not take into economic cost consideration. Therefore, this paper focuses on finding the optimal production efficiency of different temperatures and time based on the performance analysis.

Charnes, Cooper and Rhodes firstly proposed the data envelopment analysis (DEA) model in 1978 [11]. In recent decades, the DEA model has been widely used for the performance estimation of chiller systems [12], Chinese Ethylene Industries [13] and petrochemical process [14]. However, each decision-making unit (DMU) of the DEA model takes into its own circumstance in the assessment account to get the optimal efficiency, so the weight distribution of input-output factors are unreasonable [15,16]. Meanwhile, when there are less DMUs and more input-output factors, the efficiency discrimination of the DEA model is poor [17,18]. Thus the DEA cross-model (DEACM) is presented to estimate the performance index of DMUs by Sexton in 1986 [19]. Because all DMUs were ensured to be efficient with the fixed cost allocated using the DEACM method, Du et al. allocated fixed costs and resources of all DMUs as extra input measures [20]. Lim et al. apply the DEACM to stock portfolio selection in the Korean stock market, and demonstrate that the DEACM can be a promising tool for stock portfolio selection by analyzing the 9-year sample period from 2002 to 2011 [21]. Han et al. utilized the Malmquist production efficiency based on the DEACM to estimate and analyze the performance efficiency of ethylene production plants in China [22]. In order to estimate the performance efficiency of DMUs while dealing with the uncertain input-output samples, the fuzzy DEACM is used to estimate the performance of healthcare systems in a region of Southern Italy and Chinese ethylene production plants [23,24]. However, because there are too many optimal values for too many productions optimizing target, the DEACM method cannot get the optimum benchmarking.

Generally, the mean method and the optimal index method are used to get the benchmark of the performance [25]. However, the two methods do not take into weight distribution and the influence of different temperatures account. Therefore, the analytic hierarchy process (AHP) is applied to obtain the benchmark of different efficient DMUs under different temperatures based on the reasonable weight allocation and attain the real reason of the efficient DMUs. The AHP based on crisp appraisal proposed by Saaty [26] is well applied to performance estimation of ethylene production system [27] and heat pump system [28]. Han et al. analyzed and estimated the energy efficiency of petrochemical processes using DEA integrating AHP approach [29]. Yagmur studied the multi-criteria evaluation and priority analysis for localization equipment in a thermal power plant based the AHP [30].

Considering the shortages of the conventional DEA model, this paper proposes a DEACM-AHP to analyze the performance and select the optimal temperature of ethylene cracking furnaces. Firstly, this paper analyzes the performance efficiency of the ethylene cracking furnace in different temperatures and time based on the DEACM, and then the data of 40 different temperatures are fused by the AHP model based on the entropy weight to get the benchmarking of average daily. Finally, based on the analysis above, the optimum temperature and the direction of energy saving are obtained by the DEACM to attain an improvement in the energy efficiency of the ethylene cracking furnace. This proposed method is applied to analyze and estimate the performance of ethylene cracking furnaces in the petrochemical industry. It is reasonable to find out efficiency factors of different temperatures and provide some advices about operation optimization for production improvement and energy saving.

Table 1
Structural Parameters of SL-I Cracking Furnace.

Structural parameter	Value
Tube pass	2
Arrangement	16/8
Inner diameter (m)	0.051/0.073
Outer diameter (m)	0.063/0.086
Length (m)	13.68/14.92
Tube pitch (m)	0.112/0.154
Furnace Structure	
Furnace height (m)	13.66
Furnace depth (m)	3.56
Furnace width (m)	18.94
Bottom burners	48
Sidewall burners	36
Fuel gas composition (volume fraction%)	
Hydrogen	10
Methane	80
Ethane	5
Propane	5

Table 2
Operational Conditions of Cracking Furnace.

Condition	Value
Feedstock flow (kg/h) (single tube)	890.625
Dilution steam ratio (DSR)	0.60
Coil inlet temperature (CIT) (K)	875
Coil outlet temperature (COT) (K)	1122
Coil outlet pressure (COP) (kPa)	178

2. Data analysis of ethylene cracking furnace

When there are too many samples and input-output factors or the correlation between input-output factors is high in the DEA model, the discrimination of the evaluation DMU is lowed. Meanwhile, when the efficiency distinction is low enough, the overall efficiency value and the efficiency frontier are not inaccurate and reliable [31]. Due to inaccurate effective problems in the efficiency frontier, the comprehensive judgment integrating the total weigh, the reference number and the super-efficiency value is required. Meanwhile, for the same DMUs or the same input-output factor, the increasing number of multiple input-output indexes or the decreasing number of samples make the average efficiency and the effective DMU proportion decrease [22]. Therefore, selecting the appropriate input-output indexes in the DEA or the DEACM will obtain the correct conclusion.

In order to obtain performance analysis and optimal temperature selection of ethylene cracking furnaces better, we need to introduce ethylene cracking furnace model and identify major input-output factors. The SL-I type naphtha cracker model based on the established mechanism model of ethylene cracking production yields is adopted [32]. This model includes calculating process and provides the reasonable adjustment solution of the primary reaction coefficient, as well as the solving method of balance equations, the heat transfer model and the kinetics model [32].

As shown in Fig. 1, the schematic structure of the SL-I type naphtha pyrolyzer is adopted in this paper. From bottom to top, the convection section contains the lower mixing preheater (LMPH), ultra-high pressure steam super heater (HPSSH-I and II), dilution steam super heater (DSSH), the upper mixing preheater (UMPH), feed preheat section (FPH-II), boiler watering preheating section (BWPH) and feed preheating section (FPH-I).

The structural parameters of the hearth and pyrolyzer tubes are shown in Table 1. The operational conditions of the practical SL-I type pyrolyzer are shown in Table 2. The selected cracking oils are listed in Table 3.

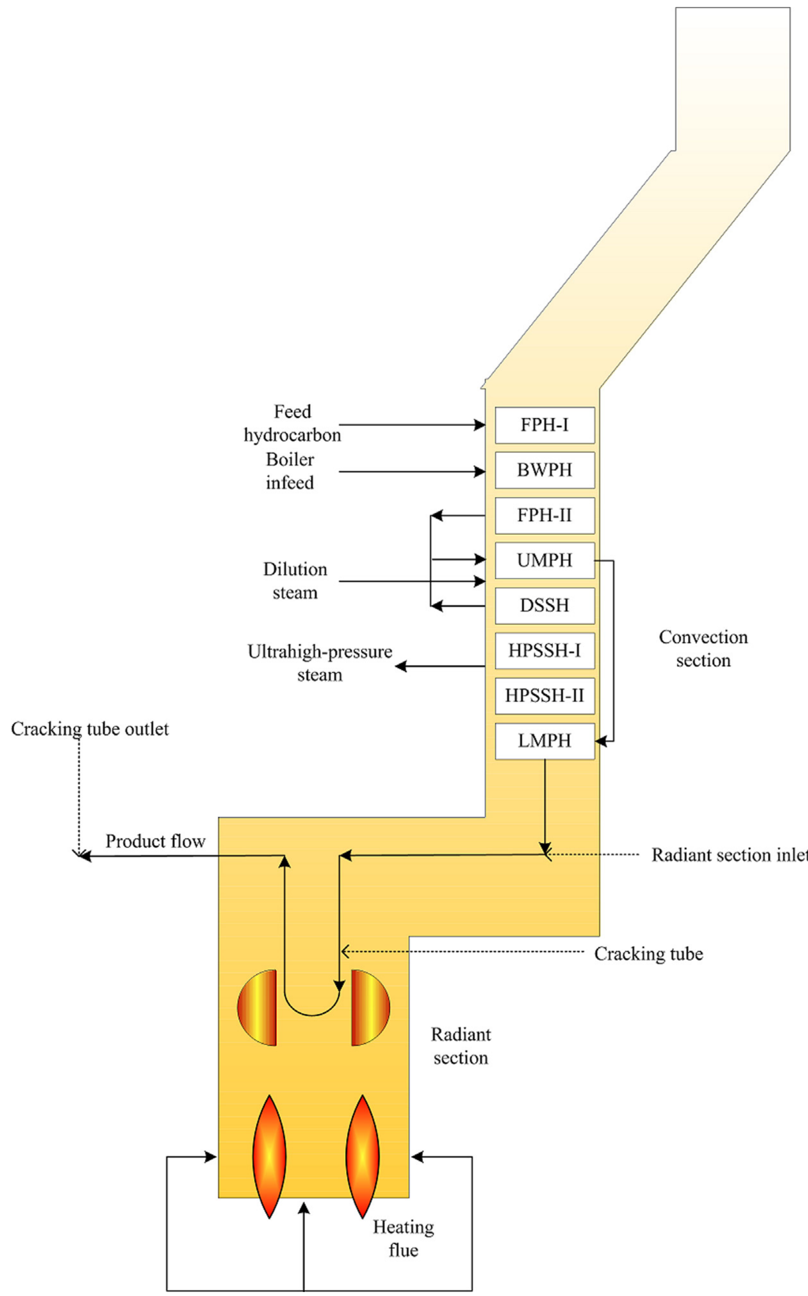

Fig. 1. Schematic structure of SL-I cracking furnace.

Table 3
Oil Character Parameters.

Oil character The relative density	Parameter	Oil character ASTM distillation range (K)	Parameter
PONA	0.7021	10%	55.9
Paraffinic hydrocarbons	0.6561	30%	73.2
Cycloalkanes	0.2639	50%	91.6
Aromatic hydrocarbons	0.08	70%	111.8
The average molecular weight (g/mol)	95.1722	90%	140.5

For ethylene cracking furnaces, the main factors directly affecting the production efficiency is the following: (1) products; (2) operation parameters; (3) feedstock. Under the real industrial process, when the feedstock is fixed, the control of product yields is achieved basically by the adjustment of temperature, which is expressed directly by the measurement of the coil outlet temperature (COT). In the ethylene cracking process, the COT decrease will make the average yield of propylene yield raise, and make the average yield of ethylene reduce. The COT has a significant effect on the yields. Therefore, the feedstock flow is selected as the input of the DEACM. The product yields, mainly including ethylene, propylene, hydrogen, methane, butylene and butane, are selected as outputs of the DEACM. The feedstock flow is fixed at 890.625 kg/h, and product yields change with COT adjustment from 1100 K to 1140 K.

3. Performance analysis and optimal temperature selection of ethylene cracking furnaces based on DEACM-AHP

The DEACM is an effective sorting method of multi-criteria decision-making using the DEA. Because the DEACM avoids the unreasonable weight distribution of multiple input-output factors of the DEA model, each effective value of the DMU can be evaluated accurately [33].

3.1. The DEACM

In the CCR (Charnes, Cooper and Rhodes) model of the DEA, there are n DMUs, x_{ji} and y_{ri} show 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. And m and s denote the number of the input and the output in the DMU. We used the following self-evaluation model (CCR) of the DEACM to evaluate each DMU_i.

$$\begin{cases} \max \dfrac{y_i^T\alpha}{x_i^T\beta} = E_{ii} \\ \dfrac{y_l^T\alpha}{x_l^T\beta} \le 1. l = 1, 2, \ldots, n \\ \alpha \ge 0, \beta \ge 0, \alpha \ne 0, \beta \ne 0 \end{cases} \tag{1}$$

Where, $x_i = (x_{1i}, x_{2i}, \ldots, x_{mi})^T > 0$, $y_i = (y_{1i}, y_{2i}, \ldots, y_{si})^T > 0. \alpha = (\alpha_1, \alpha_2, \ldots, \alpha_m)^T$ and $\beta = \left(\beta_1, \beta_2, \ldots, \beta_s\right)^T$ denote weight coefficients of m input and s output factors, respectively.

The self-evaluation model of the DEACM introduces non-Archimedean infinitesimal e and slack variables λ to obtain the input-oriented DEA in Eq. (2).

$$\begin{cases} \min[E_{ii} - \varepsilon(e_1^T\lambda^- + e_2^T\lambda^+)], \\ \sum_{i=1}^{n}\phi_i x_{ji} + \lambda^- = E_{ii}x_{ji}, j = 1, 2, \ldots, m \\ \sum_{i=1}^{n}\phi_i y_{ri} - \lambda^+ = y_{ri}, r = 1, 2, \ldots, s \\ \phi_i \ge 0, i = 1, 2, \ldots, n, \\ \lambda^- \ge 0, \lambda^+ \ge 0 \end{cases} \tag{2}$$

Where, e is used to ensure the variables strict positivity ($e_1^T = (1, 1, \ldots, 1) \in R^m$ and $e_2^T = (1, 1, \ldots, 1)^T \in R^s$). And the abstract number ε is less than any positive number and greater than 0. Usually, in order to make sure ε closing to the infinitesimal, the value of ε is set as small as possible. Meanwhile, the specific value of ε is set as large as possible to assure the convergence of computing. In this paper, ε is set as 10^{-6} to separate weakly efficient and efficient DMUs [34–37]. λ_t^- and λ_t^+ are the slack variable. $\lambda_t^- = (\lambda_t^{1-}, \lambda_t^{2-}, \ldots, \lambda_t^{m-})^T$ is the redundant amount of m input factors and $\lambda_t^+ = (\lambda_t^{1+}, \lambda_t^{2+}, \ldots, \lambda_t^{r+})^T$ is the insufficient amount of s output factors. The effective utilization degree of inputs relative to outputs E_{ii} denotes the valid value for each DMU [14]. In the DEA, if $E_{ii} < 1$, then DMU_i is deemed to the ineffective DMU, and if $E_{ii} = 1$, then DMU_i is deemed to the effective DMU.

Then the following linear programming (LP) is calculated using the self-evaluation value E_{ii} in Eq. (2) [33]:

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

Where, $i \in \left\{1, 2, \ldots, n\right\}$ and $k \in \left\{1, 2, \ldots, n\right\}$.

Based on the optimal value α_{ik}^* and β_{ik}^* in Eq. (3), the cross-evaluation value E_{ik} of the DEACM can be calculated.

$$E_{ik} = \frac{y_k^T\alpha_{ik}^*}{x_k^T\beta_{ik}^*} \tag{4}$$

Finally, the cross-evaluation matrix E in Eq. (5) is constituted by the cross-evaluation values.

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

In which the ith row of E shows the evaluation value of each DMU_i. The non-diagonal element $E_{ik}(k \ne i)$ and the main diagonal element E_{ii} denote the cross-evaluation value and the self-evaluation value, respectively. And the higher the value of E_{ik}, the better DMU_i. Thus, the mean value e_i as a criterion to measure the total evaluation of each DMU_i is shown in Eq. (6).

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

The higher e_i, the better DMU_i.

3.2. AHP model based on the entropy weight

Definition 1: Given the correlation functions of j parameters of device is $k_{ij}(x)$ in Eq. (7) (i is the i^{th} sample, $i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$)

$$k_{ij}(x) = \begin{cases} 0 & x \notin [x_j(1), x_j(4)] \\ \dfrac{x_{ij} - x_j(1)}{x_j(2) - x_j(1)} & x \in [x_j(1), x_j(2)] \\ 1 & x \in [x_j(2), x_j(3)] \\ \dfrac{x_j(4) - x_{ij}}{x_j(4) - x_j(3)} & x \in [x_j(3), x_j(4)] \end{cases} \tag{7}$$

In which $x_j(1)$,$x_j(2)$,$x_j(3)$,$x_j(4)$are nodes of $k_{ij}(x)$. The correlation function is called the standard correlation function.

If the second node $x_j(2)$ of the standard correlation function overlap in the third node $x_j(3)$, then the correlation function is called the lateral correlation function [38,39].

$$k_{ij}(x) = \begin{cases} 0 & x \notin [x_j(1), x_j(4)] \\ \dfrac{x_{ij} - x_j(1)}{x_j(2) - x_j(1)} & x \in [x_j(1), x_j(2)] \\ \dfrac{x_j(4) - x_{ij}}{x_j(4) - x_j(2)} & x \in [x_j(2), x_j(4)] \end{cases} \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m \tag{8}$$

In which, $X(i)$ is the sample value of ethylene cracking furnaces at time of $t = i$. The lateral correlation functions is adopted here, and $x_j(2)(j = 1, 2, \ldots, m)$ represent the average value. We can obtain the information matrix as follows:

$$K_{n\times m} = \begin{bmatrix} k_{11} & k_{12} & \ldots & k_{1m} \\ k_{21} & k_{22} & \ldots & k_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ k_{n1} & k_{n2} & \ldots & k_{nm} \end{bmatrix} \quad (9)$$

The center normalization: $k'_{ij} = (k_{ij} - \overline{k_j})/S_j \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$.

In which $\overline{k_j} = \frac{1}{n}\sum_{i=1}^{n} k_{ij}$ and $S_j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(k_{ij} - \overline{k_j})}\,(j = 1, 2, \ldots, m)$.

And then moving the negative number to zero (and use positive zero, zero plus a positive decimal ε), $r_{ij} = k'_{ij} - t_j + \varepsilon \quad i = 1, 2, \ldots, n; j = 1, 2, \ldots, m$, where $t_j = \min(k'_{ij}) < 0\,(j = 1, 2, \ldots, m)$.

The positive matrix $R^j{}_{n\times m}$ is obtained in the following:

$$R^j{}_{n\times m} = R_{n\times m} = \begin{bmatrix} r_{11} & r_{12} & \ldots & r_{1m} \\ r_{21} & r_{22} & \ldots & r_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ r_{n1} & r_{n2} & \ldots & r_{nm} \end{bmatrix} \quad (10)$$

We calculate the n-dimension matrix COR by $R^j{}_{n\times m}$.

$$COR = RR^T = \begin{bmatrix} o_{11} & o_{12} & \ldots & o_{1n} \\ o_{21} & o_{22} & \ldots & o_{2n} \\ \ldots & \ldots & \ldots & \ldots \\ o_{n1} & o_{n2} & \ldots & o_{nn} \end{bmatrix} \quad (11)$$

For the symmetric matrix COR, calculating the entropy of each index:$e_i = -\frac{1}{\ln n}\sum_{j=1}^{n}(r_{ij}\ln r_{ij})(i = 1, 2, \ldots, n)$. where the entropy is a measure of the difference of index data in the symmetric matrix COR. If $r_{i1} = r_{i2} = \ldots = r_{ij} = \frac{1}{n}\,(j = 1, 2, \ldots, n)$, then e_i equals to the max 1. Obviously, the entropy of index data is smaller, the difference is greater, and the important degree of index is greater in the comprehensive evaluation. On the contrary, the important degree of index is smaller in the comprehensive evaluation [40].

The important degree of each index is its weight:

$$w_i = \frac{1-e_i}{\sum_{i=1}^{n}(1-e_i)}(i = 1, 2, \ldots, n) \quad (12)$$

Using W to integrate programme, we get the X_{ref} as the fusion data:

$$X_{ref} = X^T W = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1m} \\ x_{21} & x_{22} & \ldots & x_{2m} \\ \ldots & \ldots & \ldots & \ldots \\ x_{n1} & x_{n2} & \ldots & x_{nm} \end{bmatrix}^T \begin{bmatrix} w_1 \\ w_2 \\ \ldots \\ w_n \end{bmatrix} \quad (13)$$

3.3. Performance analysis and optimal temperature selection of ethylene cracking furnaces

The data used in this study are collected by day, form the SL-I type naphtha cracker model based on the established mechanism model of ethylene cracking production yields [32]. The feedstock flow is fixed at 890.625 kg/h, and product yields change with COT adjustment from 1100 Kelvin (K) to 1140 K. The feedstock flow of the ethylene cracking furnace is taken as the main input of the DEACM, and the output (the product yields, mainly including methane, ethylene, hydrogen, propylene, butylene and butane) of the ethylene cracking furnace are taken as outputs of the DEACM.

The flow chart of DEACM-AHP for performance analysis of the ethylene cracking furnace under different temperatures is shown in Fig. 2.

Based on the self-evaluation model of Eq. (2) in the first step of the DEACM, the DEA efficiency values of three COTs with 1110 K, 1120 K and 1130 K of all day are 1, which indicates that the self-evaluation of these production statuses are effective. However, it is difficult to distinguish the pros and cons of multi production statuses every day under different temperatures based on the self-evaluation model of the DEACM.

ALL of the results of self-evaluation from the DEACM are 1 which can't be used to distinguish the performance efficiency of different temperatures and time. Therefore, the cross-evaluation value of the DEACM can get the performance efficiency value of different temperatures and time, which are shown in Figs. 3–5 respectively.

It can be seen from Figs. 3–5 that the efficiency value is growing gradually in the first few days. Because the coking rate is changing from big to small which makes the ratio of conversion changing from low to high, as the input of the model is fixed, the efficiency is growing with the rising of conversion ratio.

The production cycle of different COT is different, which means the different coking rate. The furnace has to stop periodicity for decoking if the layer of coke is too thick.

While the COT is low, because of the coking, the efficiency of the heat-transfer gets lower and lower up to time to make the conversion ratio smaller and smaller. And when its influence is over which brings by the reducing of the coking rate, the efficiency will curve a parabola. When the COT is medium, the influence of coking rate and heat-transfer together rich the balance so the curve get straight and flat. When the COT is high, the influence of coking rate is bigger and the curve keeps growing.

Although the production cycle gets shorter as the COT gets higher, it doesn't means the product yield will also get smaller. To find the optimum, an AHP based method is used. The weights of different temperatures from 1101 K to 1140 K based on the AHP are showed in Fig. 6.

Based on the optimal productive benchmarking of every day and the weight under different temperatures from 1101 K to 1140 K, we can obtain the optimal production and average benchmarking (the fusion value) values based on the DEACM as shown in Fig. 7.

It can be seen from Fig. 7 that the energy efficiency is best under the temperatures from 1114 K to 1127 K, and that of other temperatures is not well. This is mainly because when the furnace and the raw material are fixed, the efficiency of cracking furnace is determined by COT. When consider simply the reactions, if the COT is low, the cracking depth is insufficient and the raw material will not get fully utilized, while the COT is too high, some reaction not expected to happen will happen which will reduce the product yield of ethylene and propylene. When taken into the influence of coking into consideration, the high temperature will speed up the coking reactions to make the furnace be decoked more frequently, while the low temperature will make every period itself less efficient.

Based on the main input-output data of the ethylene cracking furnace with the temperatures from 1114 K to 1127 K, we obtain that the average input of the feedstock flow is 890.625 Ton, and the average product yields, mainly including ethylene, propylene, hydrogen, methane, butylene and butane, of the ethylene cracking furnace are 1.01, 16.02, 4.80, 3.88, 27.61, 13.13, respectively. For example, the average product yields of the temperatures from 1101 K to 1113 K and from 1128 K to 1140 K are shown in Fig. 8.

It can be seen from Fig. 8 that the main product yields of propylene and ethylene from 1101 K to 1113 K and from 1128 K to 1140 K lees than that of the best temperatures. If we can study the main input-output data of the best efficiency value and the best temperature from 1114 K to 1127 K, the production of ethylene under

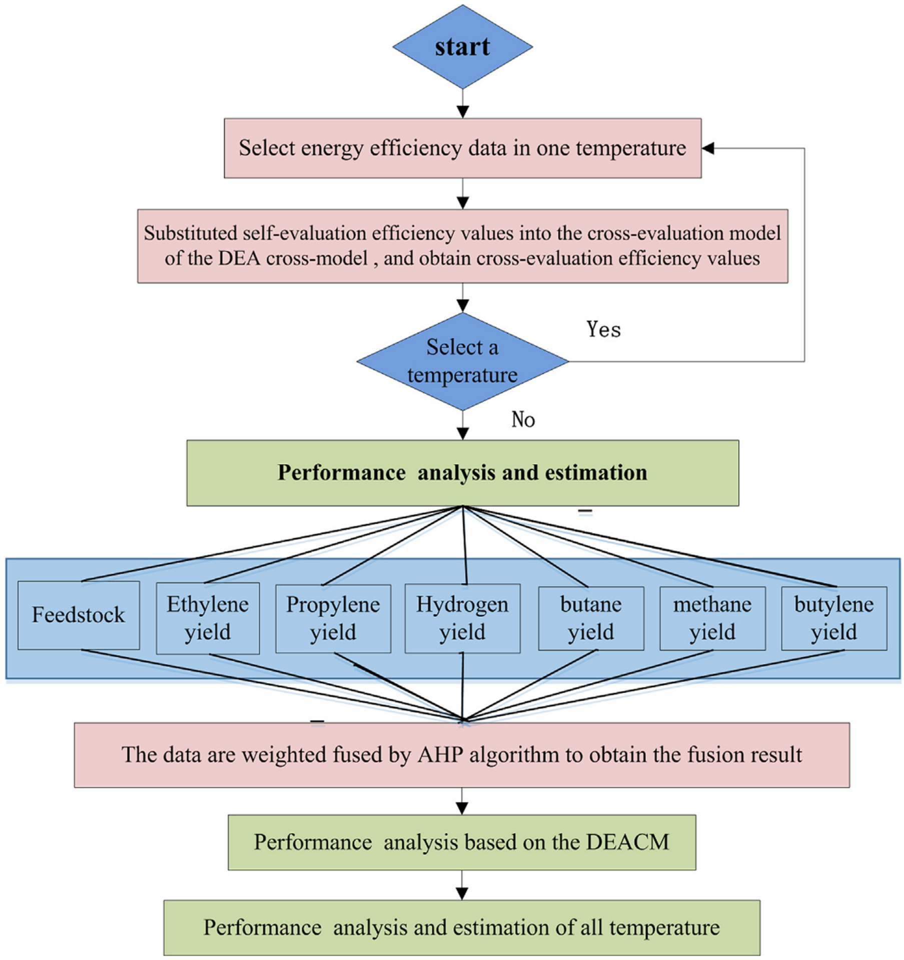

Fig. 2. The flow chart of DEACM-AHP for performance analysis of the ethylene cracking furnace.

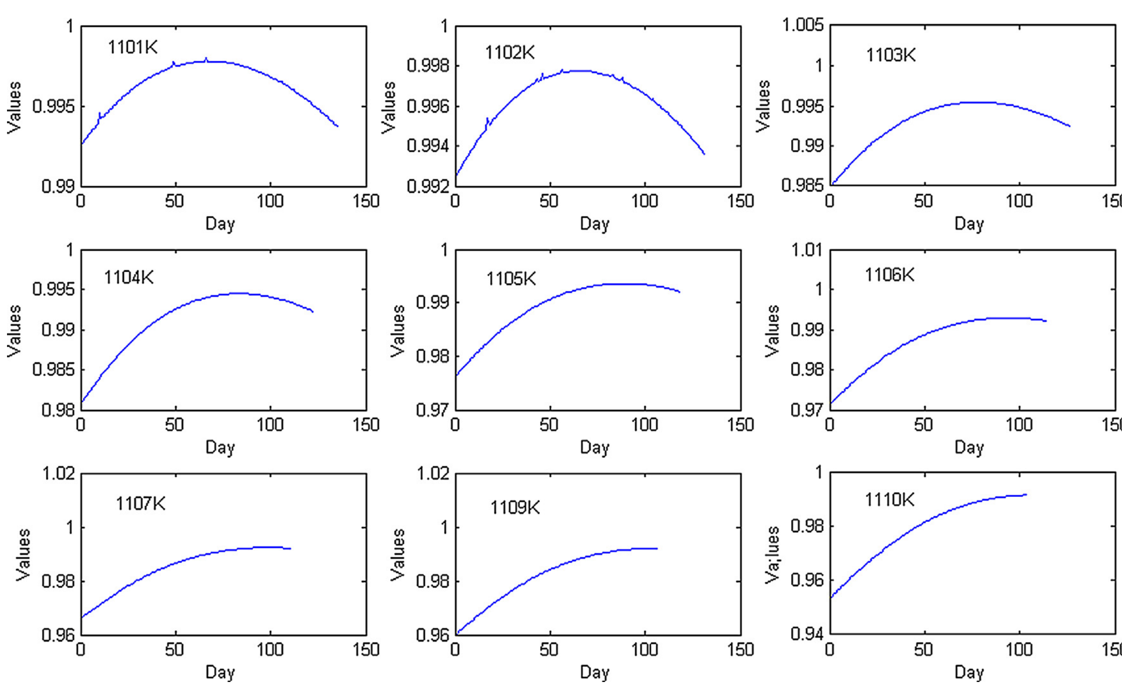

Fig. 3. The DEACM efficiency values of temperatures from 1101 K to 1110 K.

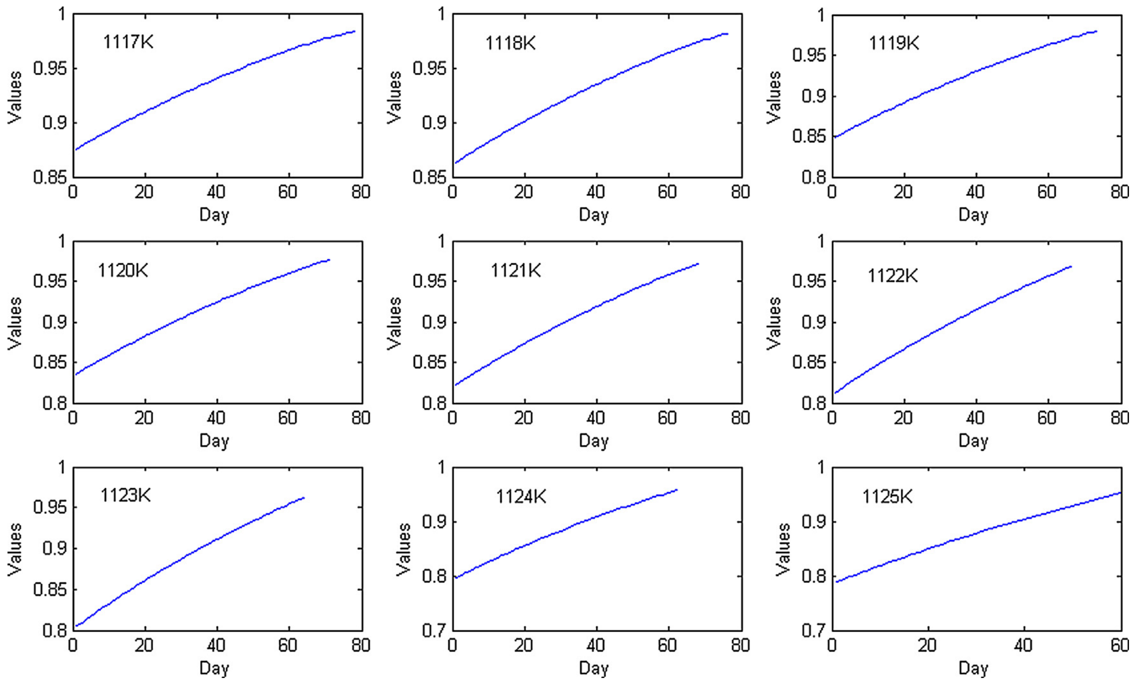

Fig. 4. The DEACM efficiency values of temperatures from 1117 K to 1125 K.

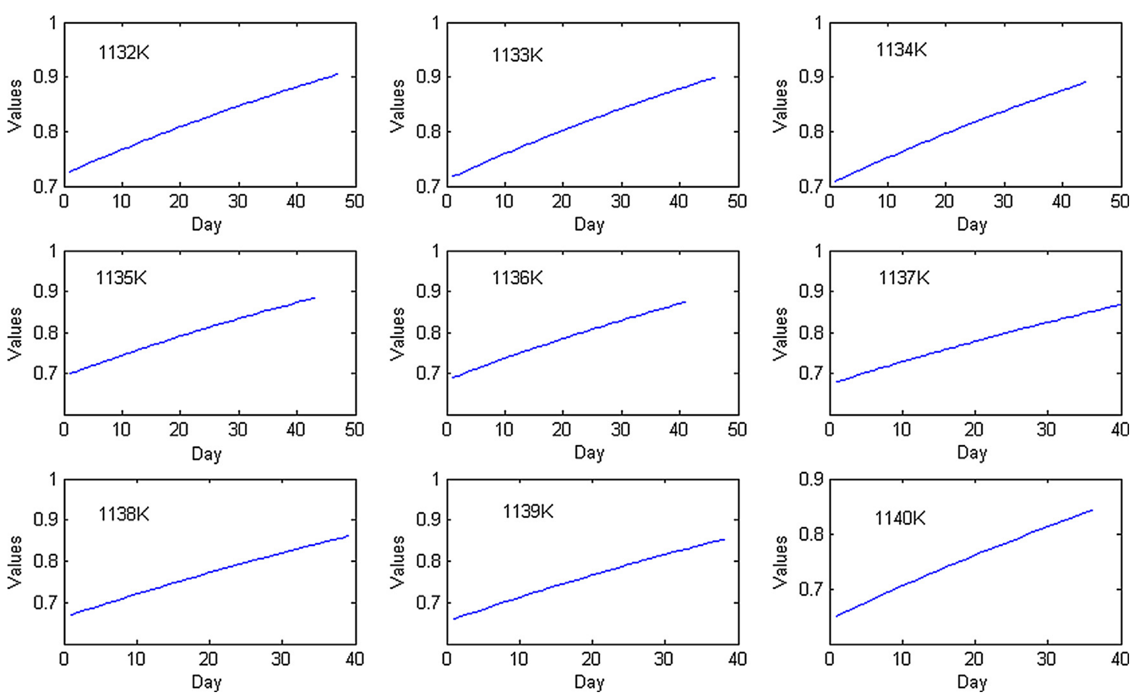

Fig. 5. The DEACM efficiency values of temperature from 1132 K to 1140 K.

other temperatures will be archived to the optimal. The temperature range is consistent with the operating condition 1122 K given in the literature [32], and the fact validated the proposed method. Meanwhile, it can reduce the consumption of fossil fuels and obtain the more effective products (ethylene and propylene) based on the quantitative of the crude oil.

4. Discussion

First, the performance analysis method of ethylene cracking furnaces based on the improved DEACM-AHP is proposed. The proposed method avoids the impact of the unreasonable weight distribution of multiple input-output factors and can attain the

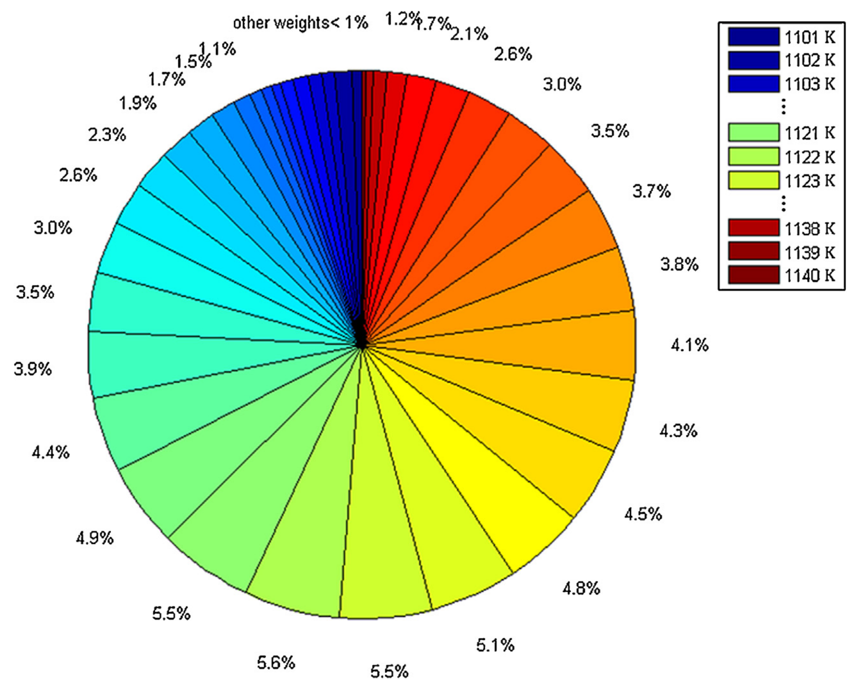

Fig. 6. The weights of different temperatures from 1101 K to 1140 K based on the AHP.

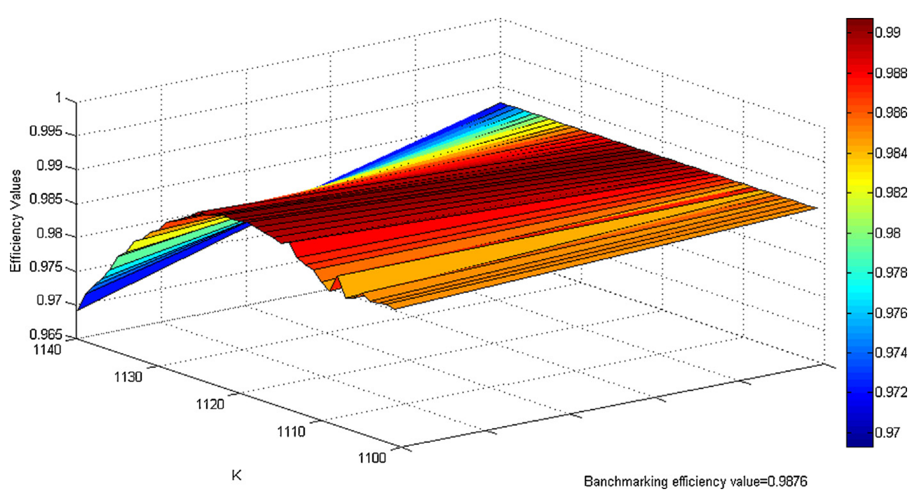

Fig. 7. The optimal production and average benchmarking values.

higher efficiency discrimination in distinguishing the performance status of all DMUs.

Second, this proposed method is applied to estimate and analyze the performance and the optimal temperature of ethylene cracking furnaces in the ethylene plant. The optimum temperature and the direction of energy saving are obtained by DEACM to attain an improvement in the energy efficiency of ethylene cracking furnaces. Meanwhile, it is reasonable to find out efficiency factors of different temperatures and provide the operation optimization for production improvement and energy saving.

Third, the proposed performance analysis modeling method is applied to optimize the energy status and get the optimal temperature of ethylene cracking furnaces effectively. However, the outputs cannot be separated into useful and useless outputs of ethylene cracking furnaces. Therefore, we will improve our model that the input and output can be separated reasonably, such as designing a self-adapting DEACM-AHP model, which is more suitable to the real world application.

5. Conclusion

This paper proposed a DEACM-AHP method to calculate performance values of the ethylene cracking furnace with different temperatures. Firstly, this paper analyzes the energy efficiency of the cracking furnace daily in different temperatures based on the DEACM. Second, we use the AHP to fuse the data of 40 different temperatures together to get the benchmarking of average daily. Finally, based on the analysis above, the optimum temperature and the direction of energy saving are found out to improve the performance efficiency of the ethylene cracking system. Meanwhile, the performance analysis result objectively indicates the ethylene performance trends of ethylene cracking furnaces under different temperatures, pointing out

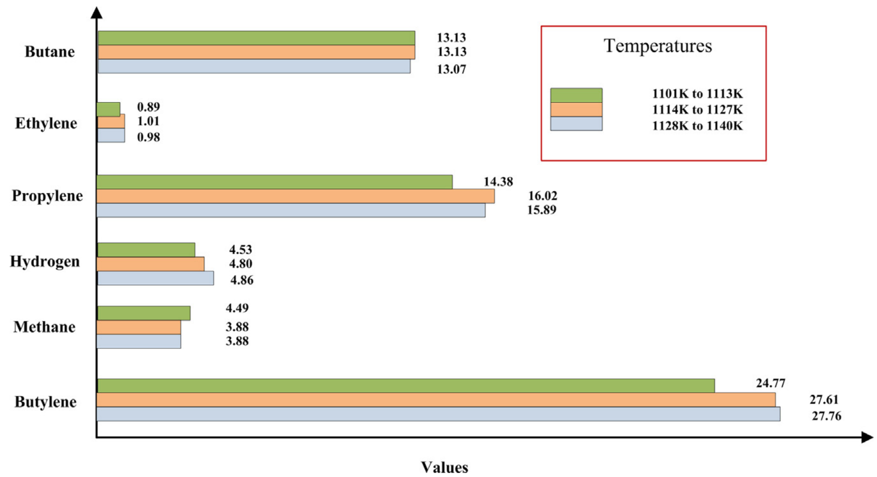

Fig. 8. The comparison result of different temperatures.

the direction and opportunity of energy saving to help ethylene production decision-makers further enhance improvement measures. It proves the effectiveness and applicability of the proposed method.

In our further research, we will introduce the economic development and environmental planning to analyze the performance efficiency of ethylene cracking furnaces. Moreover, The DEACM integrated the self-organizing neural network would be used to analyze the performance and select the optimal temperature of ethylene cracking furnaces to compare with the current study. Furthermore, performance analysis and optimal temperature selection of ethylene cracking furnaces could also be analyzed by the self-adapting DEACM-AHP model.

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