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Energy efficiency evaluation based on DEA integrated factor analysis in ethylene production☆

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A R T I C L E I N F O

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A B S T R A C T

Energy efficiency evaluation plays an important role in energy efficiency improvement of the ethylene production. It is observed from the actual production data that the ethylene production energy efficiency often varies with the complex production working conditions. In the favored methods for energy efficiency evaluation, DEA models may show poor resolution when directly used to evaluate the efficiency values. Therefore, a new energy efficiency evaluation method for ethylene production is proposed based on DEA integrated factor analysis with respect to operation classification. Three key factors, including raw material composition, cracking depth and load rate, are taken into account in determining the production working conditions by means of *k*-means algorithm. Based on the multi-working conditions mode the energy efficiency evaluation of the ethylene production is made by using DEA model, where the most related energy data are screened by factor analysis. Furthermore, the supporting decision of energy efficiency improvement is provided to the operators. The accuracy and effectiveness of the proposed method are illustrated by applying in a practical ethylene production, which gives more effective energy efficiency evaluation in the complicated working conditions of ethylene production with declined dimension of input indicators.

1. Introduction

To keep competitive and achieve sustainability, ethylene industry, which constitutes a large portion of the petrochemical industry, is required to improve its energy efficiency [1]. Therefore, the increment of energy efficiency for ethylene production has attracted growing attention worldwide, especially in China. The 2014 national bureau of statistics reports that the average comprehensive energy consumption of ethylene in China is as high as 816.6 kgoe$\cdot$t^{-1} (Kilograms of Oil Equivalent per ton), 1.63 times higher than the average level of Middle-East region, the international advanced level [2]. In 2015, the comprehensive energy consumption per ton of ethylene has only a 0.1% drop compared with that in 2014.

The above figures suggest that ethylene production industry in China demands energy conservation. Energy conservation implies improvement of energy efficiency and energy efficiency evaluation is the precondition of implementing energy conservation [3], namely, energy saving is realized scientifically through the comprehensive evaluation of energy efficiency level in production process. It is obvious that scientific and reasonable energy efficiency evaluation of ethylene production process will be of great economic and environmental benefits for the development of petrochemical industry.

As a favored method for energy efficiency evaluation, data envelopment analysis (DEA) is extensively used to measure energy efficiency of a production unit [4]. DEA algorithm can be used in the energy efficiency evaluation in ethylene production due to the relative efficiency defined by DEA. A method for analyzing the energy efficiency in ethylene production at the whole plant level is proposed based on DEA [5]. But the traditional DEA shows poor resolution and many optimal values of DEA efficiency facing up to the complex operation and huge data in the large-scale chemical production process directly. Therefore, the researches aimed at the improvement of DEA have been carried out a lot.

To overcome the influence caused by the dimension of input and output data and the inappropriate indicators, DEA integrated PCA is presented [6]. The DEA model combined with the fuzzy mathematics is presented to distinguish the performance of decision making units (DMUs) and the improvement of relative ineffective DMUs is provided [7]. DEA integrated Interpretation Structure Model is proposed to find the dominant factors influencing the energy consumption of ethylene production process and surmount the problem of evaluation difficult caused by plenty of DMUs [8]. Energy efficiency of ethylene production

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virtual benchmarking method based on dependent function analytic hierarchy process model is proposed according to technologies, scales and data distribution of energy consumption [9].

Above all the literatures, the improvement of DEA model itself is the focus but the complex productive technology of ethylene production is ignored. The operational condition of ethylene production process is complex. Energy consumption shows obvious differences in the different conditions and the differences are huge. It is not accurate of energy efficiency assessment to lose sight of the complex ethylene productive technology and the improvement strategies of energy consumptions based on energy efficiency evaluation cannot meet the requirements of different working conditions and achieve optimizing the development of petrochemical industry.

Therefore, the energy efficiency evaluation is based on the operation classification in this paper. DEA algorithm is applied respectively into the different working conditions of ethylene production and improvement strategies of energy consumption based on the multi-working conditions are provided. The data screening procedure is applied before DEA for the low resolution of DEA efficiency problem caused by excessive input indicators. This evaluation strategy with respect to the operation classification realizes an in-depth, accurate and comprehensive analysis of energy efficiency in ethylene production process.

There's one point needed to be attention to is that the values calculated by DEA are based on the concept of relative efficiency, which has different physical explanations according to the selection of input and output data. The relative efficiency means comprehensive energy consumption for unit output of product when the inputs are energy resources and the outputs are the product yield while the relative efficiency is explained as "energy" utilization efficiency when the input and output parameters selected are all energy resources. The former, that is comprehensive energy consumption for unit output of product, is the definition of energy efficiency in this paper.

The remainder of the paper is organized as follows. Section 2 reviews the DEA model, factor analysis and k-mean clustering algorithm respectively. Section 3 expounds the central idea of the proposed method. Section 4 gives a case study about energy efficiency evaluation based on the multi-working conditions in an actual ethylene production. Finally, Section 5 gives the concluding remarks.

2. Methodology

2.1. Data envelopment analysis

DEA is a method based on the concept of relative efficiency and uses the convex analysis and linear programming as the tool to estimate effectiveness of DMUs according to the input and output data [10]. The main advantage of DEA is that it allows for efficiency evaluation of multiple inputs and outputs without assigning weights and specifying any function form.

Two DEA models named CCR (Charnes, Cooper and Rhodes) and BCC (Banker, Charnes and Cooper) are used to evaluate overall technical efficiency and pure technical efficiency respectively [11]. The relationship of them is that the overall technical efficiency equals the product of pure technical efficiency and scale efficiency.

There are n supposed DMUs and each DMU has the same m inputs and s outputs. The input and output vectors can be expressed as follows.

$$\boldsymbol{X}_j = \left[x_{1j}, x_{2j}, \ldots, x_{mj}\right]^{\mathrm{T}}$$

$$\boldsymbol{Y}_j = \left[y_{1j}, y_{2j}, \ldots, y_{sj}\right]^{\mathrm{T}}$$

where x_{mj} is the m-th input of the j-th DMU, y_{sj} is the s-th output of the j-th DMU.

So for the j-th evaluated DMU, the efficiency value obtained by the CCR-DEA model can be expressed as the fractional programming in Model (1) [12].

$$\max \frac{\boldsymbol{u}^{\mathrm{T}} y_0}{\boldsymbol{v}^{\mathrm{T}} x_0} \quad \text{s.t.} \begin{cases} \dfrac{\boldsymbol{u}^{\mathrm{T}} y_j}{\boldsymbol{v}^{\mathrm{T}} x_j} \le 1. j = 1, 2, \ldots, n \\ \boldsymbol{u} \ge 0, \boldsymbol{v} \ge 0 \end{cases} \tag{1}$$

where $\boldsymbol{u} = (u_1, u_2, \ldots, u_s)^{\mathrm{T}}$, $\boldsymbol{v} = (v_1, v_2, \ldots, v_m)^{\mathrm{T}}$ are the weight coefficients of the m inputs and s outputs.

For convenience of calculation and following evaluating work, the Model (1) can be transformed as an equivalent problem linear programming model and non-Archimedean infinitesimal ε is introduced. So the CCR-DEA with non-Archimedean infinitesimal ε is shown as Model (2).

$$\begin{aligned} &\min\left[\theta - \varepsilon\left(\boldsymbol{e}^{\mathrm{T}} S^{-} + \boldsymbol{e}^{\mathrm{T}} S^{+}\right)\right] \\ &\textstyle\sum_{j=1}^{n} X_j \lambda_j + S^{-} = \theta X_0 \\ &\text{s.t.} \quad \textstyle\sum_{j=1}^{n} Y_j \lambda_j - S^{+} = Y_0 \\ &\quad \lambda_j \ge 0, j = 1, 2, \ldots, n \\ &\quad S^{-}, S^{+} \ge 0 \end{aligned} \tag{2}$$

where θ, λ_j are the dual variables; $\boldsymbol{e}^{-}$, $\boldsymbol{e}^{+}$ are the m and n dimension unit vectors; and S^{+}, S^{-} are the slack variables.

And the BCC-DEA with non-Archimedean infinitesimal ε is shown as Model (3) [12].

$$\begin{aligned} &\min\left[\theta - \varepsilon\left(\boldsymbol{e}^{\mathrm{T}} S^{-} + \boldsymbol{e}^{\mathrm{T}} S^{+}\right)\right] \\ &\textstyle\sum_{j=1}^{n} X_j \lambda_j + S^{-} = \theta X_0 \\ &\textstyle\sum_{j=1}^{n} Y_j \lambda_j - S^{+} = Y_0 \\ &\text{s.t.} \quad \textstyle\sum_{j=1}^{n} \lambda_j = 1 \\ &\quad \lambda_j \ge 0, j = 1, 2, \ldots, n \\ &\quad S^{-}, S^{+} \ge 0 \end{aligned} \tag{3}$$

where θ, λ_j are the dual variables; $\boldsymbol{e}^{-}$, $\boldsymbol{e}^{+}$ are the m and n dimension unit vectors; and S^{+}, S^{-} are the slack variables.

CCR model is based on the constant returns to scale (CRS) for the efficiency while BCC model is variable returns to scale (VRS) [12]. In the practical application of ethylene production energy efficiency evaluation, the annual ethylene yield and production scale of the domestic ethylene production enterprise that is an example of energy efficiency evaluation are fixed. In addition, this paper studies the comprehensive energy efficiency evaluation of ethylene production process and the overall technical efficiency, namely, the absolute DEA effective should be considered. Therefore, the concept of CCR efficiency that is in accordance with the actual existing state of the stable operation of ethylene production is more appropriate than BCC model in this paper.

CCR model shows that the input X_0 should be tried to ensure to increase or decrease in the same proportion when the output Y_0 of the j_0-th DMU remains constant. So the judgments of the CCR dual model with non-Archimedean infinitesimal ε can be obtained [12]: if $\theta^0 < 1$, the evaluated DMUs are relatively ineffective; if $\theta^0 = 1$, the evaluated DMUs are at least the weak relatively effective.

2.2. Factor analysis

In the actual energy efficiency evaluation, input and output indicators are so many and there is a complex relationship among the indicators. The performance of DEA model depends on the input and output data [13]. If the number of input data can be reduced by some means, the performance of DEA can be improved. Factor analysis is such a data screening method to solve this problem.

Factor analysis was presented in 1900s by K. Pearson and C. Spearman. Factor analysis refers to a kind of statistical technique which extracts the common factors from the variable group. The characteristics of this method are: the number of factors is less than the number of