Chinese Journal of Chemical Engineering 23 (2015) 2029–2036

Contents lists available at ScienceDirect

Chinese Journal of Chemical Engineering

journal homepage: www.elsevier.com/locate/CJChE

Energy consumption hierarchical analysis based on interpretative structural model for ethylene production☆

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ARTICLE INFO

Article history:
Received 20 May 2015
Received in revised form 30 June 2015
Accepted 17 July 2015
Available online 10 November 2015

Keywords:
Partial correlation coefficient
Interpretative structural model
Energy consumption
Hierarchical analysis
Ethylene production
Chemical processes

ABSTRACT

Interpretative structural model (ISM) can transform a multivariate problem into several sub-variable problems to analyze a complex industrial structure in a more efficient way by building a multi-level hierarchical structure model. To build an ISM of a production system, the partial correlation coefficient method is proposed to obtain the adjacency matrix, which can be transformed to ISM. According to estimation of correlation coefficient, the result can give actual variable correlations and eliminate effects of intermediate variables. Furthermore, this paper proposes an effective approach using ISM to analyze the main factors and basic mechanisms that affect the energy consumption in an ethylene production system. The case study shows that the proposed energy consumption analysis method is valid and efficient in improvement of energy efficiency in ethylene production.

1. Introduction

Petrochemical industry is one of the highest energy consumption sources such as power, fresh water, fuels, and steam. Ethylene production plays an important role in petrochemical industry. In 2008, the ethylene production capacity of Sinopec Corporation was 6359.4 kt and the energy consumption of ethylene plants was 649.36 kg $\cdot$ t^{-1} standard oil [1]. Petro China Company Ltd. had 2676 kt product with 714 kg $\cdot$ t^{-1} standard oil [2]. The energy consumption is much higher than that in the developed countries, so there is a huge space to improve the energy efficiency in ethylene industry [3]. The energy consumption analysis for ethylene production can bring a good economic benefit.

In recent years, reduction of energy consumption and emission in ethylene production has been highly concerned. Energy-saving situations are improved by using advanced control techniques, optimized operation conditions, and ancillary facilities [4–7]. The energy consumption in ethylene industry can be reduced by energy management and process integration [8,9]. However, the implementation procedure is complicated and tedious, and the effect can be verified only with practical projects or particular process simulations.

Tang evaluated the economic benefit of various light hydrocarbon resources for ethylene plant using a process industry modeling system [10]. Zhu *et al.* proposed energy consumption analysis based on data fusion strategy [11–13]. Xu *et al.* studied energy consumption and emission for an ethylene plant with different start-up strategies by plant-wide dynamic simulations [14,15]. These data-driven based efficiency analyzing approaches can give good results, but they ignore the effect of raw materials, which are strongly related to energy consumption, especially in ethylene production processes.

To avoid these drawbacks, it is necessary to have a more effective analysis method for energy consumption by integrating the process knowledge and simulation results, as well as the data-driven methods, with less complexity and cost of analysis and more reliable evaluation.

In 1973, Warfield developed the interpretive structural model (ISM) to analyze complex systems [16]. The barriers in a hierarchical structure of production service system, supply chains and quality management were analyzed with ISM [17–20]. Govindan *et al.* used the ISM to analyze the third party reverse logistics provider [21]. These results proved the practicality and effectiveness of ISM. Ethylene production is a complex industrial process with a lot of variables, so ISM can be used to construct a hierarchy model based on energy consumption data. It can utilize accessible daily operation data to establish reliable variable correlations, making the energy consumption analysis more reliable, while the complexity of modeling can be avoided.

The initial step to establish an ISM is to create an adjacency matrix using experts' experience, with shortcoming of subjectivity and inconsistency. The ISM of energy consumption for an ethylene plant is

☆ Supported by the National Natural Science Foundation of China (61374166, 6153303), the Doctoral Fund of Ministry of Education of China (20120010110010), and the Fundamental Research Funds for the Central Universities (YS1404, JD1413, ZY1502).
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http://dx.doi.org/10.1016/j.cjche.2015.11.011
1004-9541/

constructed based on date-driven method with process knowledge and mechanism model. In data analysis, Yu *et al.* have found that the partial correlation function is more realistic to reflect the relationship among variables [22]. Vargha *et al.* discussed interpretation problems of the partial correlation with non-normally distributed variables [23]. Fan *et al.* used the correlation coefficient method to verify the efficiency of signed directed graph model [24]. Other researchers studied the partial correlation coefficients and achieved positive results in the closed-loop optimal experiment, permutation test, and copula function modeling [25–27]. Therefore, based on the adjacency matrix of correlation coefficients and partial correlation coefficients, the reachability matrix can be obtained, and then the ISM can be applied for energy consumption in ethylene production systems.

By analyzing a large number of accessible daily operation data and considering the complexity of an ethylene plant in modeling process, we propose an effective approach using ISM based on the partial coefficients to analyze the main factors and basic mechanisms affecting the energy consumption. A case study is used to evaluate the proposed energy consumption analysis method.

2. ISM Based on Partial Correlation Coefficients

The ISM is based on the partial coefficient analysis for different elements. It can find the relationship among variables, avoid influences of irrelevant variables, and remove influences of subjective factors. The ISM is built with data-driven based analysis, because the procedure to obtain adjacency matrix is objective and consistent.

2.1. The partial correlation coefficient matrix

The correlation coefficient based approach only considers the relationship between two variables, so it is seldom used to infer the relationship between variables directly. Moreover, other factors with the relationship should be considered. By contrast, the partial correlation relationship deducts or fixes the effect of other variables beside the relationship of two variables. The linkages of variables are evaluated by partial correlation coefficients [5]. The greater the absolute value of a partial correlation coefficient is, the stronger the relationship between two variables will be. It reflects the correlation between dependent and independent variables, with the number between −1 and 1. Hence, we use its absolute value generally.

Let x_i $(i = 1, 2, \ldots, m)$ be the ith value of variable x, then the correlation coefficient of x_i and y_i is

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

where $\overline{x}$ and $\overline{y}$ are the mean values of x and y, respectively.

The correlation coefficient matrix is

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

Its inverse matrix $\boldsymbol{c}$ is used to obtain the partial correlation coefficient matrix.

$$\boldsymbol{c} = \mathrm{inv}(r) = \begin{bmatrix} c_{11} & c_{12} & \ldots & c_{1n-1} & c_{1n} \\ c_{21} & c_{22} & \ldots & c_{2n-1} & c_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ c_{m1} & c_{m2} & \ldots & c_{m-1n-1} & c_{mn} \end{bmatrix}_{m\times n.} \tag{3}$$

The partial correlation coefficient between two variables is

$$R_{ij} = -\frac{c_{ij}}{\sqrt{c_{ii}\times c_{jj}}} \quad (i = 1, 2, \ldots, m; j = 1, 2, \ldots, m). \tag{4}$$

There are different definitions about whether the partial correlation coefficient is related in different industries. Table 1 shows the relationship and the scope of partial correlation coefficients [28].

Table 1
The scope of partial correlation coefficient

Partial correlation coefficient	Relationship between two variables
$0 \le \lvert R_{ij}\rvert < 0.1$	No relationship
$0.1 \le \lvert R_{ij}\rvert < 0.3$	Low correlation
$0.3 \le \lvert R_{ij}\rvert < 0.5$	Medium correlation
$0.5 \le \lvert R_{ij}\rvert < 0.8$	Strong correlation
$0.8 \le \lvert R_{ij}\rvert \le 1$	Extremely strong

2.2. ISM

When R_{ij} is a positive number and greater than the threshold value, $a_{ij} = 1$ and $a_{ji} = 0$ is the adjacency value of x_i to x_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.

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \ldots & a_{1n-1} & a_{1n} \\ a_{21} & a_{22} & \ldots & a_{2n-1} & a_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ a_{n1} & a_{n2} & \ldots & a_{n-1n-1} & a_{nn} \end{bmatrix}_{n\times n.} \tag{5}$$

Let

$$\boldsymbol{E} = \begin{bmatrix} 1 & 0 & \ldots & 0 & 0 \\ 0 & 1 & \ldots & 0 & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & 0 & \ldots & 0 & 1 \end{bmatrix}_{n\times n} \tag{6}$$

be a $n \times n$ identity matrix, and we have

$$\boldsymbol{A}+\boldsymbol{E} = (\boldsymbol{A}+\boldsymbol{E})^2 = \ldots = (\boldsymbol{A}+\boldsymbol{E})^{n-1} = (\boldsymbol{A}+\boldsymbol{E})^n \tag{7}$$

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

$$\boldsymbol{R} = \begin{bmatrix} R_{11} & R_{12} & \ldots & R_{1n-1} & R_{1n} \\ R_{21} & R_{22} & \ldots & R_{2n-1} & R_{2n} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ R_{n1} & R_{n2} & \ldots & R_{n-1n-1} & R_{nn} \end{bmatrix}_{n\times n.} \tag{8}$$

Definition 1. In the ith row $\boldsymbol{R}_i$ $(i = 1, 2, \ldots, n)$ of reachability matrix $\boldsymbol{R}$, if $R_{ij} = 1$ $(j = 1, 2, \ldots, n)$, then element R_{ij} is added into the reachable set, expressed as $\boldsymbol{S}_i$.

Definition 2. In the jth column $\boldsymbol{R}_i$ $(j = 1, 2, \ldots, n)$ of matrix $\boldsymbol{R}$, if $R_{ij} = 1$ $(i = 1, 2, \ldots, n)$, then element R_{ij} is added into the first set, expressed as $\boldsymbol{B}_j$.

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

2.3. The ISM based on partial correlation coefficient

The ISM based on partial correlation coefficient is described as follows.

Step 1: Obtain the correlation coefficient matrix $\boldsymbol{r}$ using Eqs. (1) and (2).
Step 2: Establish the partial correlation coefficient matrix using the inverse matrix of r from Eqs. (3) and (4).