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Energy Efficiency Estimation Based on Data Fusion Strategy: Case Study of Ethylene Product Industry

Zhiqiang Geng,[†] Yongming Han,[†] Xiangbai Gu,[†,‡] and Qunxiong Zhu*,[†]

[†]College of Information Science & Technology, Beijing University of Chemical Technology, Beijing 100029, China

[‡]Sinopec Engineering, Beijing 100029, China

ABSTRACT: Data fusion is an emerging technology to fuse data from multiple data or information of the environment through measurement and detection to make a more accurate and reliable estimation or decision. In this Article, energy consumption data are collected from ethylene plants with the high temperature steam cracking process technology. An integrated framework of the energy efficiency estimation is proposed on the basis of data fusion strategy. A Hierarchical Variable Variance Fusion (HVVF) algorithm and a Fuzzy Analytic Hierarchy Process (FAHP) method are proposed to estimate energy efficiencies of ethylene equipments. For different equipment scales with the same process technology, the HVVF algorithm is used to estimate energy efficiency ranks among different equipments. For different technologies based on HVVF results, the FAHP method based on the approximate fuzzy eigenvector is used to get energy efficiency indices (EEI) of total ethylene industries. The comparisons are used to assess energy utilization states of different equipments and technologies. It is helpful to decision-makers to identify quantitative energy consumptions and major influence factors to improve energy-saving chances. Furthermore, the proposed strategy can be used to evaluate energy efficiencies in other process units too.

1. INTRODUCTION

Recently, energy conservation and emission reduction is one of the most focused topics by all countries in the world. Energy-saving has been political law in the national developing strategy of most countries. The petrochemical industry is one of the highest energy consumption sources, using power, fresh water, fuels, steam, and so on. The ethylene product process or system is one of the most important equipments in the petrochemical industry, especially for the down chemical products such as polyethylene, glycol, grain alcohol, rubber, etc. The high temperature steam cracking for producing ethylene is one of the most important process technologies in the petrochemical industry, for example, the famous Lummus, S&W, Linde, and KBR technology.[1,2] However, it is one of the highest energy consumption equipments of petrochemical industry.[3,4] In recent years, the steam cracking process has been relatively mature, and no large improvements have been made in cracking furnace structures and process techniques. So many ethylene plants and vendors are pursuing low cost, large scales, multiraw materials, energy-saving, and optimization to get the biggest benefit.

Data fusion initially comes from Multisensor Data Fusion (MDF), which is an emerging technology to fuse data from multiple sensors to make a more accurate estimation of the environment through measurement and detection.[5] Data fusion techniques combine data from multiple data, and related information in associated databases, to achieve improved accuracies and more specific inferences than could be achieved by using a single datum alone. Up to now, data fusion techniques and systems have received significant attention and are widely used in various areas. They can be used not only in military services, but also in civilian applications such as environment surveillance, monitoring of complex industrial process, medical fault diagnosis, smart buildings, food quality, and precision agriculture. 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.[6−10] The rapid evolution of computer techniques and the maturation of data fusion technology will provide a foundation for utilization of data fusion in different applications.[11−13]

The Analytic Hierarchy Process (AHP) was developed by Saaty in the 1970s.[14,15] It is a subjective tool to analyze and transfer the qualitative criteria into quantification and to generate alternative priorities with nine scales. In actual applications, nine linguistic scales per variable can be truncated to seven or five linguistic terms for simplifications. The AHP enables decision makers to analyze structure complex problems in a simple hierarchical form and to assess a large number of quantitative and qualitative factors in a systematic manner. It breaks down complicated decision-making problems into several hierarchies through merging quality and quantity analysis. The comprehensive decision weights for each alternative are calculated by the weight sum. It is widely used in many areas, including the best policy selection, the assessment of alternatives, the allocation of resources, the prediction of outcomes, the optimization and resolution of decision conflicts, etc. The literature applied the AHP approach to assess national competitiveness in the hydrogen energy technology sector.[16,17] Also, national long-term improvements were established in energy efficiency and GHG control plans related to Korea's energy policy.[18,19] However, inputs and outputs of real world problems are often imprecise in reality,

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and it is very difficult to tackle them with crisp numbers reflecting human's appraisals related to pairwise comparisons. The traditional AHP method is unable to provide the crisp values needed to properly reflect the fuzziness associated with decision-making problems in the real world. For the classic multiattribute decision-making, eigenvectors can be used to determine the weights of attributes. The problem is how to construct a fuzzy attribute evaluation matrix and calculate eigenvectors. The proposed Fuzzy AHP (FAHP) method will focus on how to develop decision matrix information and define weights of all attributes on the basis of the fuzzy multiattribute eigenvector method.[20]

This Article puts forward an integrated framework of the energy efficiency estimation based on data fusion strategy according to technologies, scales, and data of energy consumption including fuels, power, steam, and water within an ethylene process boundary. A Hierarchical Variable Variance Fusion (HVVF) algorithm and a Fuzzy Analytic Hierarchy Process (FAHP) method are proposed to estimate energy efficiencies of ethylene equipments. For different equipment scales with the same process technology, the HVVF algorithm is proposed to obtain energy consumption indictors and estimate energy efficiency ranks among different equipments. For different technologies based on HVVF results, the FAHP method based on the approximate fuzzy eigenvector is used to get energy efficiency indices, which can be viewed as virtual benchmarks of total ethylene industries. The applications of ethylene equipments and the energy consumption estimation and analysis for the whole ethylene industry are tested. It is helpful for decision-makers to identify the quantitative energy consumption targets and major influence factors to improve energy utilization states. At the same time, the proposed method can be used in other process units to evaluate energy consumption levels too.

2. PRELIMINARIES ON ENERGY CONSUMPTION OF ETHYLENE EQUIPMENT

2.1. Energy Boundary of the Ethylene Product System. In the ethylene industry, different ethylene plants may be quite different in the division of the energy utilization boundary. To make a unanimous criterion of computing the energy efficiency objectively, we refer to the ethylene industrial standards (DB37/751-2007) and national standards for energy consumption (GB/T2589-2008) in China.[21,22] The energy utilization boundary of ethylene product system is described in Figure 1.

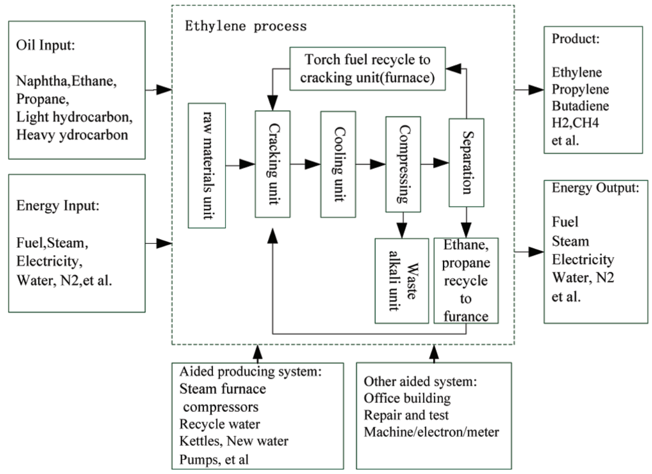


Figure 1. Energy utilization boundary of the ethylene product process.

The ethylene utilization boundary is defined in the dashed rectangle including the raw materials unit, high temperature cracking unit (furnace), cooling unit, and compressing and separation unit, which produces the main ethylene and propylene, and other byproducts. The main energy types are as follows: the water including recycled water, industrial water, and boiler water; the power; steams including superhigh pressure steam, high pressure steam, middle, and low pressure steam; fuels; and N_2 and compressing air. Because of the lowest consumption of N_2 and compressing air among energy types, they were not computed in energy efficiencies of the ethylene product process. According to the statistics, the energy consumption fees are up to more than 50% of the total cost for the ethylene product process. Most ethylene plants only use the Special Energy consummation (SEC) as the energy efficiency index. SEC is described as how much energy consumption is needed when producing one ton ethylene, GJ/T ethylene.

Generally, the energy consumption is easily affected by raw materials composition, process technologies, equipment scales, and load varieties, respectively. The SEC is only obtained by summing consumptions of water, steams, powers, and fuels. Although the SEC reflects the energy consumption level to some extent, it is quite simple and unilateral without considering relevant affecting factors as above-discussed. Because the SEC index endows each energy type with the same weight, it cannot totally reflect the states of different energy types. So we use the data fusion method to get energy efficiency indices by considering different energy types and factors. Energy efficiencies of the water, power, steams, and fuels are analyzed through endowing with different weights among them, according to process technologies, equipment scales and feed materials compositions. The SEC is just one of the energy consumption types in our method.

2.2. Energy Efficiency Index. In this Article, the Energy Efficiency Index (EEI) is used to estimate energy consumption levels of ethylene equipments. In industry, the most commonly used definition for energy efficiency is the amount of energy consumed per unit of product or output, also called the Energy Intensity Factor (EIF), which expresses the amount of energy used to produce the given products. To be informative and useful, energy efficiencies must be compared to something (another unit, company, over time), and for comparison there must be rules. In the case of comparing energy efficiency, it is especially important to define system boundaries so that all users are speaking equally as discussed in section 2.1. The energy efficiency is considered mainly from the perspective of a single industrial company and from the perspective of a production site, grouping several production processes/units. However, the best energy efficiency for a site is not always equal to the sum of the optimum of the energy efficiency of the contained production processes or units. Deoptimization of the energy efficiency of one or more production processes or units may be required to achieve the optimum energy efficiency of the site, to show how the energy efficiency is developed over time in a plant, or to make benchmarks between different plants.

The main purpose of the energy efficiency indicators is to be able to monitor the progress of the energy efficiency of a given production unit over time. The other purpose is to see the impact of energy efficiency improvement measures and projects on the energy performance of the production process.

The EIF can be defined as:

$$\mathrm{EIF} = (\text{energy imported} - \text{energy exported})/\text{products produced} \quad (1)$$

EIF is a number with dimensions, for example, GJ/ton. The EEI is defined by dividing a reference energy intensity factor by the energy intensity factor as follows:

$$\mathrm{EEI} = \mathrm{EIF_r}/\mathrm{EIF} \quad (2)$$

$\mathrm{EIF_r}$ can either be a reference number, which is generally accepted by the industry sector to which the production process belongs, or can be the energy intensity factor of the production process at a given reference year. As for the ethylene product process, EIF is the consumption of each energy type of every unit product (ethylene) in one statistical period. $\mathrm{EIF_r}$ is the reference benchmark of energy consumption for each energy type. So every EEI of energy type can be defined as:

$$\mathrm{EEI}_i = \mathrm{EIF}_{ir}/\mathrm{EIF}_i \quad (3)$$

The EEI of SEC can be written as:

$$\mathrm{EEI_{sec}} = \frac{\mathrm{EIF_{secr}}}{\mathrm{EIF_{sec}}} = \frac{\sum_{i=1}^{m} \mathrm{EIF}_{ir}}{\sum_{i=1}^{m} \mathrm{EIF}_{i}} \quad (4)$$

In formulas 3 and 4, if EEI is more than 1, then the energy efficiency is high, otherwise it is low. Yet the problem is how to get $\mathrm{EIF_r}$ to compute EEI. In most ethylene plants, they often are obtained by an experience value of historical energy consumptions, or a statistical value, or an energy policy reference value. The reference value of EIF is very subjective, vague, and inaccurate, and it cannot reflect energy consumption trends. Therefore, we use the data fusion method to compute $\mathrm{EIF_r}$ to get EEIs of the same process technology with different equipment scales. Furthermore, the EEIs of different process technologies can be obtained in total ethylene industries.

3. HVVF FOR THE SAME PROCESS TECHNOLOGY

There are about seven common process technologies in ethylene product industries, which are shown in Table 1.

Table 1. Technology Types of Ethylene Product Process

technologies	descriptions
I class	S&W front-end depropanization and front adding hydrogen technologies
II class	Lummus order separation technologies
III class	TPL patent technology
IV class	Mitsubishi heavy industries front-end epropanization and behind adding hydrogen
V class	Dalian university of technology
VI class	Linde front-end deethanization technologies
VII class	KBR front-end depropanization and front adding hydrogen technologies

The same process technology of ethylene product systems has different equipment scales. Through exploiting energy consumption data, we can find that the relationship between energy consumptions and scales is linear or similar without considering the cracking raw materials and process structures. For different technologies, because of natural differences among process technologies, such as the process structures, feedstock, styles of energy usage, the process operational set-points, etc., the energy consumption relationships among different technologies are nonlinear. So the HVVF cannot be used to estimate energy efficiencies for the different technologies. It can be used to get the reference $\mathrm{EIF_r}$ based on the variances of energy consumption types among different scales in the same process technology.

The data characteristics are demonstrated often with noise and abnormal data in a statistical period. Therefore, data processing methods are used to obtain the real values of energy consumption data, to ensure the accuracy and consistency of the data.

3.1. Abnormal Data Detection.

Abnormal data samples are either very different or inconsistent from other normal data samples, which express the abnormality of the spatial position and data items relationships. So those isolated points or outliers in the spatial position deviating from the groups can be deleted. In probability theories, when the variable X obeys a normal distribution or an approximate normal distribution, the random variables with high probabilities will appear in the neighborhood of $E(X)$, while those with small probabilities will appear in the distance of the $E(X)$. When X is far from $E(X)$, it can be regarded as outliers and be removed. The specific formula is shown in formula 5:

$$|x_{ij}(k) - \bar{x}_{ij}| > 2S_{ij} \quad (5)$$

$$\text{s.t.}\ \bar{x}_{ij} = \frac{1}{N}\sum_{k=1}^{N} x_{ij}(k),\ S_{ij} = \sqrt{\frac{1}{N-1}\sum_{k=1}^{N}(x_{ij}(k) - \bar{x}_{ij})^2},\ i = 1, 2, ..., m;\ j = 1, 2, ..., n$$

If the $x_{ij}(k)$ satisfies formula 5, then remove it. At the same time, the consistency test of data is dealt with via Grubbs criteria in different devices. The specific formula is shown as follows: If $T_j(k) \geq T(n,\alpha)$, then remove $x_{ij}(k)$. Where n is the number of data, α is the significant level.

$$T_j(k) = \frac{|x_{ij}(k) - \overline{x_j(k)}|}{S_j(k)} \quad (6)$$

$$\text{s.t.}\ \overline{x_j(k)} = \frac{1}{N}\sum_{i=1}^{N} x_{ij}(k),\ S_j(k) = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_{ij}(k) - \overline{x_j(k)})^2},\ j = 1, 2, ..., n;\ k = 1, 2, ..., N$$

3.2. Data Normalization.

Data normalization refers to the proportion of data at a certain scale, so the data can fall into a small specific region. For this theme, different variables may work in different types; some variables have the positive effect on the theme by using the following transformation:

$$x'_{ij} = \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (7)$$

Some variables have the negative effect on the theme, using the following transformation:

$$x'_{ij} = 1 - \frac{x_{ij} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} = \frac{x_j^{\max} - x_{ij}}{x_j^{\max} - x_j^{\min}} \tag{8}$$

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

3.3. HVVF Algorithm. In practice, most ethylene plants choose a month or a quarter as a statistical period to explain the energy consumption. Of course, we can choose smaller periods such as a day or a week, even an hour. However, because the small period may not reflect situations of the energy efficiency for the unstable operation, the longer period is better to estimate the energy efficiency than is the small period. The sampling data set is recorded each day, and then the mean values of different energy consumptions are computed monthly. The main idea of HVVF algorithm is according to the variances of energy types between different ethylene equipment scales. Specially, if the equipment scales are the same, then energy consumption data will be summed together and the mean values computed, respectively. We have collected energy consumption data sets from ethylene plants of about seven technologies in Table 1 from 2001 to 2010, as shown in Figure 2.

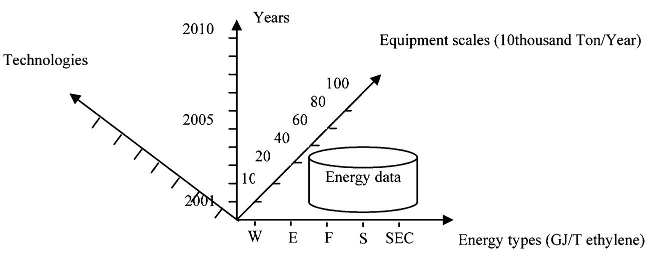


Figure 2. Compositions of energy consumption data.

In Figure 2, the capital letter W, E, F, and S are the initial letter of water, electricity, fuel, and steam, respectively. For different technologies, the equipment scales do not include all of the series from 10 to 100; for example, the S&W technology has only 20, 80, and 100 product scales in selected ethylene plants. According to the definition of multisensor data fusion, every energy consumption data set of different energy types can be viewed as different "sensors" of measurement variables. The fusion process is thus divided by two hierarchies to get the reference EIFr, monthly and yearly. The energy efficiency estimation can be made by the results of data fusion to monitor the energy efficiency states, such as the year-on-year growth rates, the annual growth rate, and so on.

The first hierarchy fusion is for monthly energy consumption data, and different energy types fusion functions are made by formula 9.

$$F_i(k) = \sum_{j=1}^{N} w_j x_{ij}(k),\ w_j = \frac{(\sigma_{ij})^2}{\sum_{i=1}^{n} (\sigma_{ij})^2},$$
$$\sigma_{ij} = \sqrt{\frac{1}{N} \sum_{j=1}^{N} (x_{ij}(k) - \frac{1}{N} \sum_{j=1}^{N} x_{ij}(k))^2},\ N = 30 \tag{9}$$

where i is the energy type, W, E, F, S, and SEC; k is the number of ethylene plants with the same technology. $x_{ij}(k)$ is the energy consumption data. w_j is the weights. σ_{ij} is the variances.

For different ethylene plants with the same technology, fusion functions of energy types are made by formula 10.

$$MF_i(k) = \sum_{i=1}^{n} w_k F_i(k),\ w_k = \frac{(\sigma_{ki})^2}{\sum_{k=1}^{K} (\sigma_{ki})^2},$$
$$\sigma_{ki} = \sqrt{\frac{1}{K} \sum_{i=1}^{K} (F_i(k) - \frac{1}{K} \sum_{i=1}^{K} F_i(k))^2} \tag{10}$$

The second hierarchy fusion is to get the energy fusion of one year, 12 months, and made by formula 11.

$$YF_i(k) = \sum_{i=1}^{n} w_i MF_i(k),\ n = 12,\ w_i = \frac{(\sigma_{ki})^2}{\sum_{k=1}^{K} (\sigma_{ki})^2},$$
$$\sigma_{ki} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (MF_i(k) - \frac{1}{N} \sum_{i=1}^{N} MF_i(k))^2},\ N = 12 \tag{11}$$

Next, the specific data fusion steps are described as follows.

Step 1: Select energy consumption data sets of an ethylene process technology for one year.
Step 2: Data preprocessing, that is, abnormal detection and data normalization above-discussed.
Step 3: Use formulas 9 and 10 to get the monthly fusion EIF_r value of every different energy type.
Step 4: Use formula 11 to get the yearly fusion EIF_r value of every different energy type.
Step 5: Use formula 3 to get the energy efficiency index of every energy type.
Step 6: Similarly, the EIF_r values and energy efficiency indices of other years can be obtained with the same technology.
Step 7: Repeat steps 1−6, so we can get the EIF_r values and energy efficiency indices of other technologies.

3.4. A Case Study. In Table 1, one of the technologies was taken as an example to test the hierarchy variance fusion method. The ethylene product process with a selected technology has five plants, including two equipments with 200 000 tons/year, two equipments with 800 000 tons/year, and one scale with 1 000 000 tons/year equipment. According to the hierarchical variance fusion steps, the first hierarchy fusion results every month can be obtained, in which only are listed from January 2007 to December 2008 as examples. The second hierarchy fusion results every year can be obtained for about 10 years from 2001 to 2010. The two hierarchy fusion results of energy consumption were described in Figures 3 and 4. In the same way, we can get other technologies' energy consumptions and know clearly the states of energy consumptions among different equipments. Furthermore, we can monitor the different energy types' efficiency states, and compare their energy efficiencies with each other to improve the energy usage of the ethylene product process.

In Figures 3 and 4, we can find that the fuel and SEC are decreasing trends with year-on-year. Multienergy consumption trends analysis and efficiencies estimation can acquire much

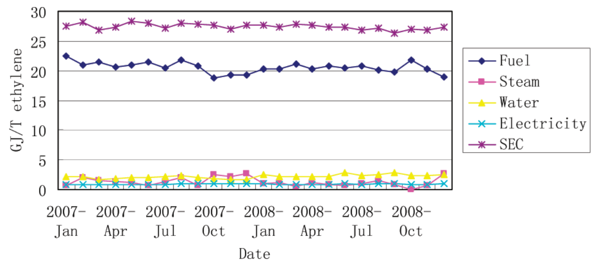


Figure 3. Trends of different energy types from 2007 to 2008.

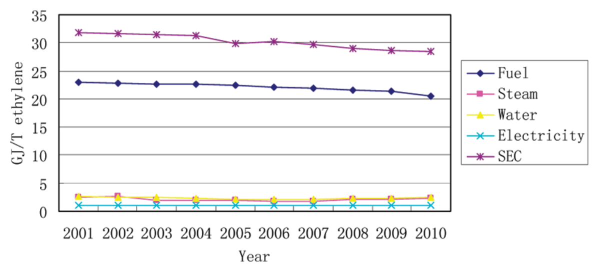


Figure 4. Fusion results of one technology from 2001 to 2010.

more information than only SEC. The monitoring results in some statistical periods can give some advice to managers and operators to improve energy utilization strategies. We select two ethylene plants of the same technique to estimate and compare the differences between them. Figure 5 is the EEIs of

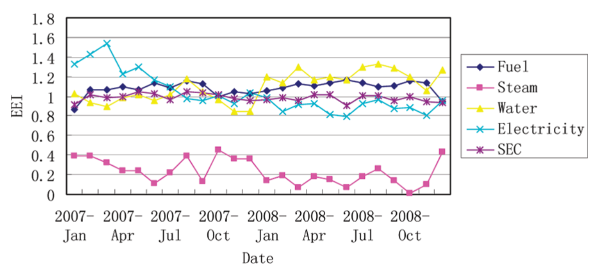


Figure 5. EEIs of the first ethylene plant.

different energy types of a selected ethylene plant, called the first ethylene plant. The fusion results can be as the reference EIF_r, and also can be viewed as a virtual benchmark. Figure 6

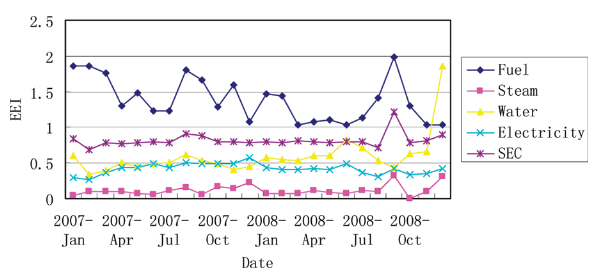


Figure 6. EEIs of the second ethylene plant.

shows the energy efficiencies of another ethylene plant, called the second ethylene plant. We can see that the energy efficiencies of the first plant are higher than those of the second plant, because the EEIs in Figure 5 are closer to or more than 1 than in Figure 6. Yet the fuel efficiency of the second plant is higher than that of the first plant.

4. FAHP OF DIFFERENT ETHYLENE PRODUCT TECHNOLOGIES

In this section, we use the FAHP to analyze energy consumptions and energy efficiencies of different ethylene technologies. Energy consumption values among different scales with the same techniques are linear or similar. The HVVF algorithm is simply and understood easily, and the fusion results are quite satisfying with comparisons of the actual ethylene plants. However, energy consumptions of ethylene equipments are affected severely by technologies, raw materials, and load varieties, and the relationships among them are quite complex nonlinear. Next, we will discuss energy consumptions and energy efficiencies of ethylene plants with different technologies.

4.1. Fuzzy Set and Fuzzy Numbers. In the real world, it is very hard to extract precise data from human judgments. Because human preferences encompass a degree of uncertainty, decision-makers may very well be reluctant or unable to assign crisp numerical values to pairwise comparison. Decisions made by the experts rely on their individual competence. Therefore, it is more appropriate to present the data by fuzzy numbers instead of crisp numbers. The concept of fuzzy theory was first introduced by Zadeh in 1965.[23] The fuzzy theory includes elements such as fuzzy set, membership function, and the fuzzy numbers used to efficiently change vague information into useful data. In many fuzzy multiattribute decision-making problems, the final scores of alternatives are represented in terms of fuzzy numbers. To choose the best alternative, we need a method to establish a crisp total ordering from fuzzy numbers. To carry out the task of comparing fuzzy numbers, many authors have proposed fuzzy ranking methods that yield a totally ordered set or ranking.

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 triangular fuzzy numbers to prioritize competitiveness in the FAHP to analyze the energy efficiencies of ethylene product process. The following definition describes the membership function of fuzzy numbers and the operations on them.

Let $\tilde{A} = (a_1,a_2,a_3)(a_1 \le a_2 \le a_3)$ and $\tilde{B} = (b_1,b_2,b_3)(b_1 \le b_2 \le b_3)$ be any two triangular fuzzy numbers. The operations laws are as follows:

$$\tilde{A}(+)\tilde{B} = (a_1, a_2, a_3)(+)(b_1, b_2, b_3) = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \quad (12)$$

$$\tilde{A}(-)\tilde{B} = (a_1, a_2, a_3)(-)(b_1, b_2, b_3) = (a_1 - b_1, a_2 - b_2, a_3 - b_3) \quad (13)$$

$$\tilde{A}(\cdot)\tilde{B} = (a_1, a_2, a_3)(\cdot)(b_1, b_2, b_3) = (a_1b_1, a_2b_2, a_3b_3) \quad (14)$$

$$\tilde{A}(/)\tilde{B} = (a_1, a_2, a_3)(/)(b_1, b_2, b_3) = (a_1/b_3, a_2/b_2, a_3/b_1) \quad (15)$$

$$\tilde{A}^{-1} = (a_1, a_2, a_3)^{-1} = (1/a_3, 1/a_2, 1/a_1) \quad (16)$$

4.2. FAHP Method. The AHP method needs the decision-making process to build a hierarchical structure of the problem. At each level of the hierarchy, the AHP uses pairwise comparison judgments and estimation matrix to identify and valuate the relative priorities of criteria and alternatives. However, the regular AHP cannot effectively consider the uncertainty of assessing and tackling a problem. For example, if experts are not able to give exact numerical values to express their opinions, a more realistic alternative option is to use linguistic assessments instead of numerical values.[24−26] In such a situation, for each variable in the problem domain, an appropriate linguistic label set is chosen and used by individuals who participate in the decision-making process to express their opinions. On the contrary, the FAHP can capture human's appraisal of fuzziness and ambiguity as making pairwise comparisons of the relative criteria and alternatives.

The proposed FAHP method will focus on how to develop decision matrix information and define weights of all attributes on the basis of the multiattribute eigenvector decision making method. The fuzzy evaluation matrix will be constructed by the fuzzy scale of pairwise comparisons in Table 2, which refers to covariance definition of random variables.[27,28] The eigenvectors of fuzzy attribute evaluation matrix are not calculated directly from a fuzzy eigenvector equation but are approximated. These eigenvectors could be adopted as optimal one-dimensional space to determine the weights of multiattribute. We used the fuzzy scale to conduct pairwise comparison judgments with regards to the relative criteria and alternatives.

Table 2. Fuzzy Scale

important scale	definition	explanation
(1, 1, 1)	equal importance	two elements contribute equally
(2/3, 1, 3/2)	moderate importance	one element is slightly favored over another
(3/2, 2, 5/2)	strong importance	one element is strongly favored over another
(5/2, 3, 7/2)	very strong importance	one element is very strongly favored over another
(7/2, 4, 9/2)	extreme importance	one element is the highest favored over another

The steps of the improved FAHP method are described as follows.

Step 1: Build up the hierarchy structure model of the problem, including the alternatives sets chosen from decision-makers, that is, the alternatives hierarchy, and the attribute sets by measuring performances of alternatives, that is, the attributes hierarchy.

Step 2: Construct the pairwise comparison judgments matrix of attributes using the fuzzy scales about the problem descriptions on the same level of the hierarchy structure.

Step 3: Construct the fuzzy numbers decision matrix. Let $A = (a_{ij})_{n\times m}$ be a fuzzy pairwise comparison judgment matrix. Let $F_{ij} = (l_{ij},m_{ij},h_{ij})(l_{ij} \le m_{ij} \le h_{ij})$ be a triangular fuzzy number. The triangular fuzzy decision matrix can be obtained using the following formula 17 based on fuzzy number operational laws formulas 12−16.

$$\tilde{F}_{ij} = \sum_{j=1}^{m} F_{ij}(/)\left[\sum_{i=1}^{n}\sum_{j=1}^{m} F_{ij}\right] = \left(\frac{\sum_{i=1}^{n}\sum_{j=1}^{m} l_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} h_{ij}}, \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} m_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} m_{ij}}, \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} h_{ij}}{\sum_{i=1}^{n}\sum_{j=1}^{m} l_{ij}}\right), \quad i = 1, 2..., n;\ j = 1, 2..., m \tag{17}$$

$$\text{s.t.} \sum_{j=1}^{m} F_{ij} = \left(\sum_{j=1}^{m} l_{ij}, \sum_{j=1}^{m} m_{ij}, \sum_{j=1}^{m} h_{ij}\right),\ \sum_{i=1}^{n}\sum_{j=1}^{m} F_{ij} = \left(\sum_{i=1}^{n}\sum_{j=1}^{m} l_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{m} m_{ij}, \sum_{i=1}^{n}\sum_{j=1}^{m} h_{ij}\right)$$

Step 4: Construct the fuzzy covariance decision matrix $\tilde{R}$. The fuzzy average $\tilde{E}_j$ and fuzzy variance s_j can be expressed by a triangle fuzzy number, respectively, $\tilde{E}_j = (l_j',m_j',h_j')$, $S_j = (l_j'',m_j'',h_j''))$, as follows:

$$l_j' = \frac{1}{n}\sum_{i=1}^{n} l_{ij},\ m_j' = \frac{1}{n}\sum_{i=1}^{n} m_{ij},\ h_j' = \frac{1}{n}\sum_{i=1}^{n} h_{ij}, \quad j = 1, 2, ..., m \tag{18}$$

$$l_j'' = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(l_{ij} - l_i')^2},\ m_j'' = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(m_{ij} - m_i')^2},\ h_j'' = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(h_{ij} - h_i')^2},\ j = 1, 2, ..., m \tag{19}$$

So the fuzzy covariance matrix of $\tilde{F}_{ij}$ can be expressed by the positive matrix:

$$\tilde{R} = \left[\frac{|l_{ij} - l_j'|}{h_j''}, \frac{|m_{ij} - m_j'|}{m_j''}, \frac{|h_{ij} - h_j'|}{l_j''}\right] = [a_{ij}, b_{ij}, c_{ij}],\ i = 1, 2, ..., n;\ j = 1, 2, ..., m \tag{20}$$

Let $CR = \tilde{R}^T\tilde{R}$, then the CR is a fuzzy symmetric positive matrix easy to define and prove.[20] We can ensure that all of the weights of eigenvectors relate to the maximum eigenvalue of m-dimensional positive fuzzy symmetry matrix.

Step 5: Compute the eigenvector of fuzzy attribute evaluation space. The approximated eigenvector in the fuzzy evaluation space CR can be calculated by the product and root method (geometry average method) as shown in formula 21. Therefore, the importance of attribute-related alternatives could be ordered objectively based on this eigenvector. This $\tilde{W}_i$ can be selected as the attribute's weight for the proposed FAHP algorithm.

$$\tilde{W}_i = \left(\frac{\alpha_i}{\gamma}, \frac{\beta_i}{\beta}, \frac{\gamma_i}{\alpha}\right),\ i = 1, 2, ..., m \tag{21}$$

$$\text{s.t.}\alpha_i = \left(\prod_{j=1}^{m} a_{ij}\right)^{1/m},\ i = 1, 2, ..., m,\ \alpha = \sum_{k=1}^{m}\alpha_k$$

$$\beta_i = \left(\prod_{j=1}^{m} b_{ij}\right)^{1/m},\ i = 1, 2, ..., m,\ \beta = \sum_{k=1}^{m}\beta_k$$

$$\gamma_i = \left(\prod_{j=1}^{m} c_{ij}\right)^{1/m},\ i = 1, 2, ..., m,\ \gamma = \sum_{k=1}^{m}\gamma_k$$

Step 6: Compute the comprehensive weights of alternatives for all attributes, which can be obtained by projection vectors to the one-dimensional space. The decision judgment weight value $W(A)$ of decision attributes can be calculated using formula 22.

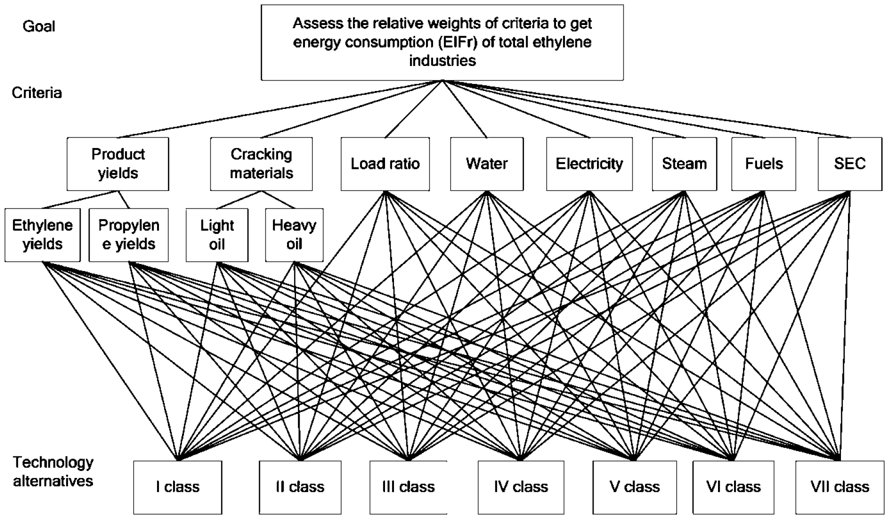


Figure 7. Hierarchy model of energy consumption evaluation for the ethylene product process.

However, the $W(A)$ is weights of different criteria, a nonfuzzy number now.

$$W(A) = \tilde{F}_{ij}(\cdot)\tilde{W}_i^T \tag{22}$$

The proposed FAHP method is relatively objective to identify the differences of criteria among alternatives, and it can trade-off the subjective marks of experts' opinions.

4.3. A Case Study. In this section, the energy consumption data fusion based on FAHP method is analyzed to acquire the EEIs in foundation of HVVF results for ethylene product systems. According to the FAHP data fusion steps described in section 4.2, we can obtain the energy consumption $\mathrm{EIF_r}$ of the total ethylene industry, which can be viewed as a virtual benchmark. Furthermore, EEIs of different energy types can be estimated for the ethylene product process. Also, the comparisons of energy efficiencies among different ethylene technologies can be obtained. The influence factors of energy consumptions also can be acquired to guide managers and operators to improve technologies or operational conditions for saving energy and emission reduction. The energy consumption data fusion process is described as follows.

Step 1: Analyze mainly the influence factors of energy consumption in the ethylene product process; the detailed introductions are described in section 2.

Step 2: For the same technology, the relevant energy consumption data are collected. The HVVF method is used to obtain the energy consumption indicators of every technology described in section 3.

Step 3: For the total ethylene industries with different process technologies, the hierarchy analysis model is built according to the FAHP method. The hierarchy model is shown in Figure 7. The goal is to get and assess relative weights of criteria and to obtain the energy $\mathrm{EIF_r}$ of total ethylene industries. The criteria are described as follows: product yields including ethylene and propylene yields, cracking materials including light and heavy oil, load ratio, water, electricity, steam, fuels, and SEC. The alternatives are common technologies used in petrochemical plants and listed in Table 1.

Step 4: For the criteria of energy consumption factors, decide the operational type and fuzzy valuation scales. The definitions of criteria are shown in Table 3.

Table 3. Operational Type for Defining Criteria and Fuzzy Scales

aspects	criteria	explanation of hierarchy comparison
product yields	ethylene yields	higher ethylene yields are more important than another
	propylene yields	higher propylene yields are more important than another
cracking materials	light oil	light oil is strongly favored over heavy oil, like naphtha, ethane, and propane
	heavy oil	heavy oil is not as important as light oil, like heavy hydrogen
load ratio	load ratio	near the design load is more important than away from the design load
water	water	more used water is moderately favored over another, considering the water (not freshwater) is enough as compared to other energies
electricity	electricity	less used electricity is strongly favored over another
steam	steam	less used steam is slightly favored over another
fuel	fuel	less used steam is the highest favored over another, considering the fuel is not renewable
SEC	SEC	less used SEC is slightly favored over another

Step 5: Select the relevant energy consumption data of ethylene product process including seven technologies, with the data of cracking materials, product yields, and load ratio. Use the FAHP steps described in section 4.2, to get the weights of criteria, and then get different $\mathrm{EIF_r}$ of energy consumptions of total ethylene industries.

Step 6: Compute the EEIs of different energy consumption from one technology, and compare with total industry virtual indicators using the EEI computing formula. We can analyze and estimate the energy efficiency status and energy consumption ranks about one technology in total ethylene industries.

Figure 8 shows the synthesis energy consumption trends of total ethylene industries based on the FAHP from 2001 to 2010. The energy consumptions or intensity factors can be viewed as $\mathrm{EIF_r}$ or virtual benchmarks of different energy consumption types. We can find the energy consumption states of the ethylene industry: the SEC is about 26.5−35.5 GJ/T ethylene, the water consumption is about 2−3.5GJ/T ethylene, the electricity consumption is about 1.2−1.5 GJ/T ethylene, the fuel consumption is about 19.3−25.4 GJ/T ethylene, and

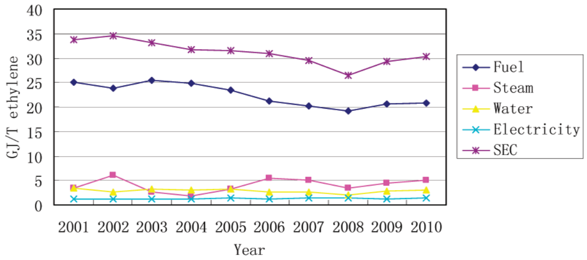
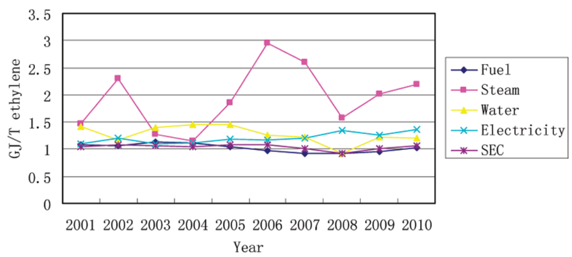


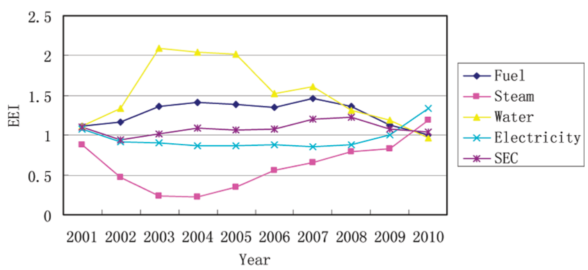
Figure 8. Energy consumption EIF_r of total ethylene industries.

the steam consumption is about 1.8−6.1 GJ/T ethylene. So distance as compared to advanced ethylene equipments can be explored.

The energy consumptions of each technology from 2001 to 2010 are obtained using the HVVF method for the same technology discussed in section 3. We can use the energy consumptions of each technology as the EIF, and the synthesis energy consumption of total ethylene industries as the EIF_r. So we can explore the energy efficiency states among different technologies, and know which technology is better. For example, in Figure 9, (a) is the energy efficiency states of



(a) EEI of one technology

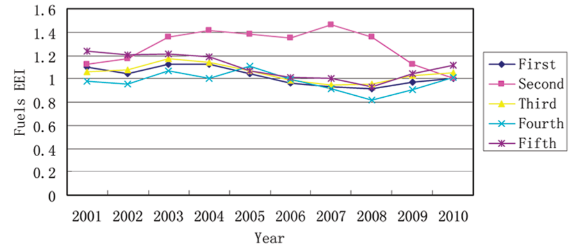


(b) EEI of another technology

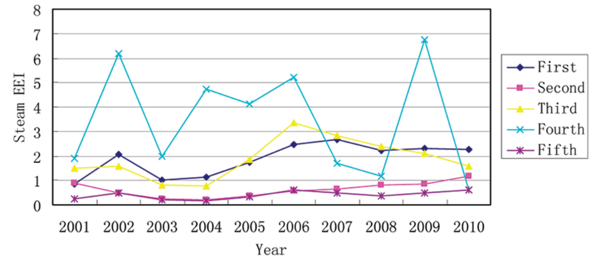
Figure 9. Comparisons of EEIs among different technologies.

one ethylene technology, and (b) is the energy efficiency states of another technology. We can find that the energy efficiency of one technology in Figure 9a is better than that in another technology, because the EEIs of fuel, water, electricity, steam, and SEC are almost more than 1. However, the water EEI and fuel EEI in Figure 9b are better than those in Figure 9a. So we can take advantage of the high energy efficiency technology to improve saving energy of the low energy efficiency technology.

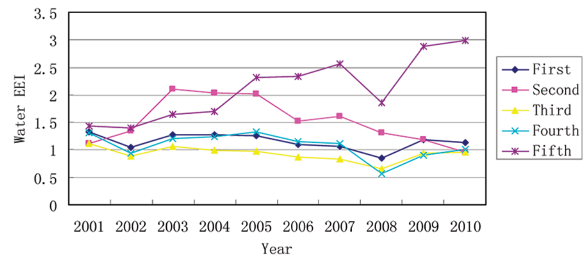
Furthermore, the EEI trends and states of five technologies are taken as examples to be analyzed in petrochemical industries for about 10 years in Figure 10. For example, in fuel EEI, the second technology is the best, the fourth technology is the worst, and others are almost equal. In steam EEI, the fourth is the best and the fifth is the worst. So we can obtain the EEIs of water, electricity, and SEC of different



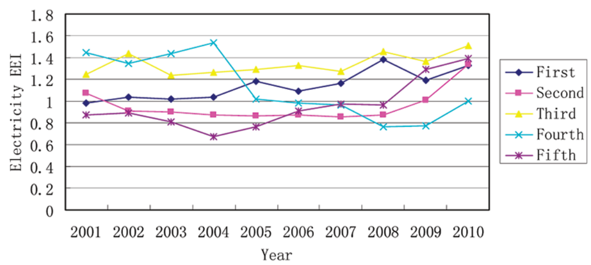
(a) Fuel EEI



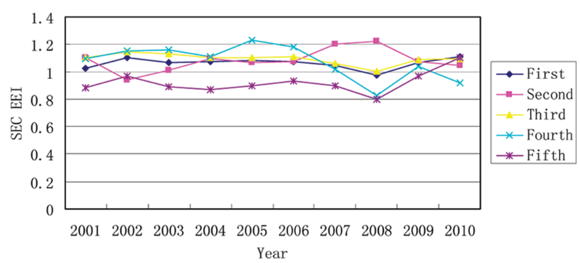
(b) Steam EEI



(c) Water EEI



(d) Electricity EEI



(e) SEC EEI

Figure 10. EEIs of the five selected technologies.

technologies, and compare their differences of technologies with each other.

Analysis results are compared to energy consumption data of the five selected ethylene plants with different technologies in one statistical period. The energy efficiency trends and states are accordant with the facts of five real ethylene plants. From an energy efficiency estimation of the total ethylene product process, we find that light cracking materials have higher EEI.

Justification and reduction of utilization of steam and fuel will have higher energy efficiency for ethylene equipments. However, the trade-off among water, electricity, and steam should be taken care of.

5. CONCLUSIONS

We applied the data fusion strategy base on integrated HVVF and FAHP approach to develop a framework for estimating and assessing the energy performance for high temperature steam cracking in the ethylene product process. The results are calculated by a scientific procedure of multicriteria decision-making approach. The study provides HVVF to obtain energy efficiency indices and an estimation of different scale equipments with the same process technology. For different technologies based on results of HVVF, FAHP based on the approximate fuzzy eigenvector method is proposed to get the energy efficiency indices (virtual benchmarks) of total ethylene industries. The optimal alternatives for establishing ethylene energy policy and estimation energy performance among different technologies were studied from economic viewpoints. The energy efficiency analysis based on data fusion strategy is helpful for the decision-maker to identify the quantitative energy consumption targets and major effecting factors to improve the energy utilization states. The policy-makers and decision-makers have to strategically focus on strengthening those high energy consumption plants management and make out reasonable EEI for total ethylene industry to improve energy-saving chances.

In our further studies, we will investigate and integrate other methods, such as data envelopment analysis, neural network, etc., to analyze the scale efficiency, input−output energy measuring of ethylene product process, and to compare with the current work. Moreover, we will apply the current developed integrated framework based on HVVF and FAHP approach to make out the EEIs or virtual benchmarks of whole ethylene product systems in the energy policy sector. Furthemore, the proposed EEI estimation method can be used in other process units for evaluating the energy consumption status.

■ AUTHOR INFORMATION

Corresponding Author

*Tel.: +86-10-64426960. Fax: +86-10-64437805. E-mail: zhuqx@mail.buct.edu.cn.

Notes

The authors declare no competing financial interest.

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