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Research Paper

Energy structure analysis and energy saving of complex chemical industries: A novel fuzzy interpretative structural model

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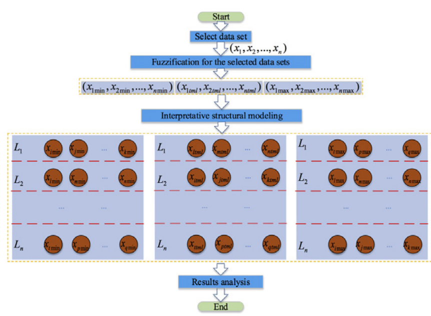
HIGHLIGHTS

- A FISM method based on the fuzzy theory is proposed.
- Energy structure and energy saving framework of complex chemical industries is obtained.
- This proposed method is efficient in energy structure analysis and energy saving of complex chemical processes.
- The raw materials can be saved about 10–30%.
- The carbon emissions can be reduced about 0.3–0.45 Ton.

GRAPHICAL ABSTRACT



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ABSTRACT

Chemical production plays a key effect in energy saving and the sustainable development. However, the uncertain data has a direct impact on the production and the energy efficiency of complex chemical industries. Therefore, in order to analyze the energy structure and improve the energy efficiency of complex chemical industries, this paper proposes a novel interpretative structural model (ISM) integrated the fuzzy theory (FISM). The production data are divided into the upper limit value, the lower limit value and the most probable value based on the data fuzzification. And then energy structures and energy saving potentials in different production configurations are obtained by using the FISM. Finally, the proposed method is applied to analyze the energy structure and obtain energy saving potentials of the ethylene production process in complex chemical industries. The experimental results show that the key impact factors of influencing the ethylene production in different production configurations can be obtained to improve the energy efficiency. Moreover, compared with the benchmarking of the best production configuration, the raw materials can be saved about 10–30% and the carbon emissions can be reduced about 0.3–0.45 Ton when producing one Ton ethylene.

1. Introduction

Nowadays, energy saving, the environmental protection and the sustainable development are paid more and more attention by human beings, especially in the complex chemical industries. The development degree of complex chemical industries has become a main sign of the industrialization process in a country. Moreover, the ethylene industry is one of the most important parts in complex chemical industries. As an industrial power, the ethylene production in China reached 17.044 million Tons in 2015 [1]. Meanwhile, the ethylene products increased around 5% per year. The change of the ethylene production in China since the 11th Five-Year is shown in Fig. 1 [1]. In 2012, the

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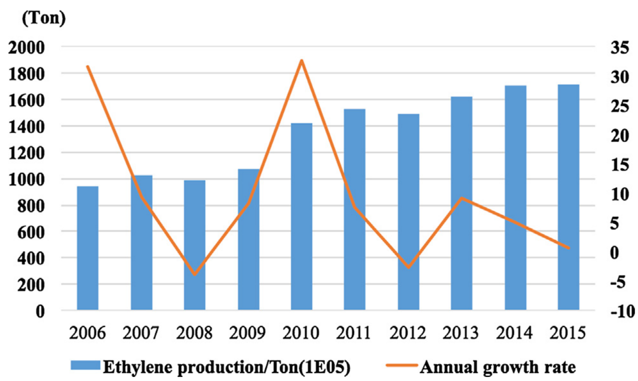

Fig. 1. Ethylene production in China.

ethylene production of China Petrochemical Corporation was 9475 kt/a, and the average fuel plus power consumption (standard oil) was 579.59 kg per Ton [2]. Energy consumptions costs of ethylene plants took up more than 50% of overall costs [3]. Although ethylene yields in China have lain in the forefront of the world, the energy efficiency still lags behind the developed countries [4]. Therefore, studying the energy structure analysis and energy saving of complex chemical industries is also beneficial for both environmental and sustainable development of the Chinese economy.

In order to analyze the energy structure and improve the energy efficiency of complex chemical industries, this paper proposes a novel energy structure analysis and energy saving method based on the ISM integrated the fuzzy set theory (FISM). First, the production data are divided into the upper limit value, the lower limit value and the most probable value based on the data fuzzification. And then the minimum eigenvalues, the most likely eigenvalues and the maximum eigenvalues are obtained. Moreover, energy structures and energy saving potentials in different production configurations are obtained by using the FISM. Finally, the proposed method is applied in the energy structure analysis and energy saving of the ethylene production process in complex chemical industries. The experimental results show that the key impact factors of influencing the ethylene production in different production configurations can be obtained to improve the energy efficiency. Moreover, compared with the benchmarking of the best production configuration, the raw materials can be saved about 10–30% and the carbon emissions can be reduced about 0.3–0.45 Ton when the ethylene is produced about one Ton.

The organization of the remaining parts is as follows: Section 2 presents the research status of the structure analysis and energy saving with the ISM and the fuzzy theory. In Section 3, the triangular fuzzy number (TFN) and the FISM are introduced in detail. The proposed method is applied in the energy structure analysis and energy saving of complex chemical industries in Section 4. Discussion and conclusion are obtained in Sections 5 and 6, respectively.

2. Related work

Nowadays, many related energy saving methods in complex chemical industries have been proposed. Zennifer et al. elaborated the importance and shortcomings of ethylene glycols in subarctic and artic regions [5]. Salkuyeh et al. proposed a novel ethylene production plant which could directly convert shale gas to ethylene with zero carbon emissions [6]. In order to attain an improvement in the overall profit, Zhao et al. optimized the production plan of the ethylene plant to save the energy [7]. Yu et al. proposed a novel multiple learning particle swarm optimization based on space transformation perturbation to improve the performance efficiency of an ethylene cracking [8]. Han et al. proposed a new linear optimization fusion model based on fuzzy C-means to analyze the energy efficiency of the ethylene production process [9]. Geng et al. applied the data fusion method to improve the energy efficiency analysis of ethylene plants. However, these methods did not take the influence of the energy consumption indicators and carbon emissions into consideration [10,11]. Meanwhile, the multi-dimensional data has a direct impact on the production and the energy efficiency of complex chemical processes [12–14]. Therefore, the energy structure analysis is beneficial for the energy saving of complex chemical industries.

The ISM was introduced by Warfield to analyze the structure of complex systems [15]. Lim et al. applied the ISM method to get the relationship of the sustained supply chain [16–18]. Dubey et al. used the total ISM to identify barriers of Green supply chain management (GSCM) [19]. Maher et al. analyzed the interaction among influential factors on the implementation of GSCM practices by using the ISM method [20]. Wu et al. used the ISM integrated the Bayesian network to attain an engineering risk factor relationship represented by a cause-effect diagram and provide the explicit risk information [21]. Venkatesha et al. proposed a new model based on the ISM for the Risk Priority Number calculation to establish interdependencies between the selective risks associated with the apparel retail supply chains [22]. In addition, Trivedi et al. used the ISM to analyze the contextual relationship among some key factors, which play an influential role in the disaster waste [23]. Yadav et al. interpreted the interdependency among the selected critical success factors based on the ISM method [24]. Han et al. applied the ISM integrated the extreme learning machine to analyze the energy efficiency and reduced the energy consumption of the ethylene industry [25].

However, the statistical data have the characteristics of multi-dimension, noise and uncertainty. Thus, it is not objective and accurate to evaluate the energy efficiency production situation of each plant based on the statistical data. Meanwhile, because the adjacency matrix of the ISM is obtained by using expert experiences and affected by the uncertain data, the results are inconclusive and not objective. Therefore, the fuzzy theory is introduced into the ISM to obtain the energy structure and energy saving potentials.

The fuzzy theory was originally proposed by Zadeh and applied in quality management and risk management [26]. Coppi et al. compared two kinds of clustering models by using the left and right fuzzy data to analyze the empirical information affected by imprecision or vagueness [27]. Chen et al. realized comprehensive and quantitative evaluation of environ-economic benefits of anaerobic digestion technology by using the fuzzy evaluation method based on life cycle assessment and cost-benefit analysis [28]. Molinari et al. presented a weak preference relation to establish a total order on the family of TFN [29]. Wang et al. used TFN to facilitate the knowledge management performance evaluation with a group support system [30]. In order to predict the nonlinear fuzzy system more precise, Wu et al. proposed a new fuzzy support vector machine with multi-dimensional input variables [31]. Based on the grey model and neural networks, Zeng et al. built the TFN grey model (TFGM) integrated the neural network to accurately forecast the TFN series [32]. Based on the distance between two TFNs, Zeng et al. constructed a fuzzy least absolute liner regression model to evaluate the fitting effect of the observed and estimated values [33]. Akbas et al integrated fuzzy set theory and quality function deployment to maintain the sustainable development at wastewater treatment plants [34]. In order to improve the ethylene production conditions and guide the efficiency of energy utilization, Han et al. introduced fuzzy data envelopment analysis cross model [35]. Based on the fuzzy grey model (FGM) and multicriteria decision making model (MCDM), Wang et al. proposed FG-MCDM to improve energy efficiency and protect environment [36]. Based on the above analysis, the energy structure of complex chemical industries can be simplified based on the ISM, and the uncertain data can be disposed by using the effective TFN in the fuzzy theory. Therefore, this paper proposes a novel energy structure analysis and energy saving method based on the FISM.

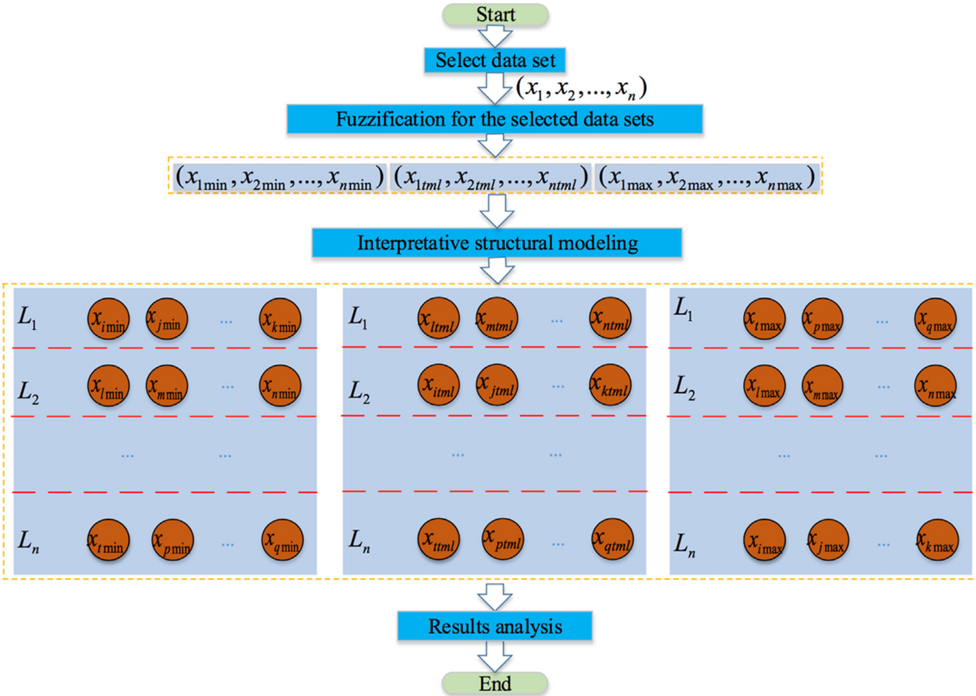

Fig. 2. The flow chart of the FISM.

3. FISM based on the TFN

3.1. Fuzzy numbers and its operations

Assume there are some statistical data named $x_1, x_2, x_3, \ldots, x_n$. And the certain amount data in a specific interval m ($0 < m \leqslant n$) is selected, which are represented as $x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+m-1}$.

The minimum value x_S, the most likely value x_M and the maximum value x_L are calculated based on Eqs. (1)–(3).

$$x_S = \min\{x_i, x_{i+1}, \ldots, x_{i+m-1}\} \tag{1}$$

$$x_M = \frac{x_i + x_{i+1} + \ldots + x_{i+m-1}}{m} \tag{2}$$

$$x_L = \max\{x_i, x_{i+1}, \ldots, x_{i+m-1}\} \tag{3}$$

And then the lower bound $x_S^{'}$ and the upper bound $x_L^{'}$ of the selected data set are calculated based on Eqs. (4) and (5) [35].

$$x_S' = \begin{cases} x_M - 2*(x_M - x_S), & x_M \geqslant 2*(x_M - x_S) \\ 0, & x_M < 2*(x_M - x_S) \end{cases} \tag{4}$$

$$x_L' = x_M + 2*(x_L - x_M) \tag{5}$$

According to the definitions of the TFN [26] and Eqs. (6)–(8), the membership grades of m data can be calculated by the triangular fuzzification.

$$\mu_S = \begin{cases} 1, & x \leqslant x_S' \\ e^{\frac{1}{2}*\left(\frac{x - x_L'}{\frac{x_L' - x_S'}{\sigma}}\right)}, & x_S' < x < \frac{x_S' + x_L'}{2} \\ 0, & x \geqslant \frac{x_S' + x_L'}{2} \end{cases} \tag{6}$$

$$\mu_M = \begin{cases} 0, & x \leqslant x_S' \\ e^{-\frac{1}{2}*\left(\frac{x - \frac{x_S' + x_L'}{2}}{\frac{x_L' - x_S'}{\sigma}}\right)}, & x_S' < x < x_L' \\ 0, & x \geqslant x_L' \end{cases} \tag{7}$$

$$\mu_L = \begin{cases} 0, & x \leqslant \frac{x_S' + x_L'}{2} \\ e^{-\frac{1}{2}*\left(\frac{x - x_L'}{\frac{x_L' - x_S'}{\sigma}}\right)}, & \frac{x_S' + x_L'}{2} < x < x_L' \\ 0, & x \geqslant x_L' \end{cases} \tag{8}$$

The selected m data $x_i, x_{i+1}, x_{i+2}, \ldots, x_{i+m-1}$ are transferred for $x_{i\min}$, x_{itml} and $x_{i\max}$ corresponding to the maximum of μ_S, μ_M and μ_L, and then it can obtain a set of triangular fuzzy number ($x_{i\min}$, x_{itml}, $x_{i\max}$), where $x_{i\min}$ represents the minimum eigenvalue (min) and x_{itml}, $x_{i\max}$ represent the most likely eigenvalue (tml) and the maximum eigenvalue (max), respectively.

3.2. The FISM

The ISM is widely applied to find the hidden relationships among different variables in modern engineering systems. Meanwhile, the adjacency matrix of the ISM based on the data-driven is objective and consistent. Moreover, the uncertain data can be disposed based on the TFN. Therefore, the FISM is used to obtain the energy structure and the energy saving potential.

3.2.1. The partial correlation coefficient matrix

The correlation coefficient can well illustrate the relation between two variables. However, due to the impact of other variables, it is seldom used to directly infer the inner relationship between variables. But the partial correlation reflects the real relationship between different variables [37]. Meanwhile, the greater the absolute value of a partial correlation coefficient is, the stronger relationship between these two variables will be. Because of the ceteris paribus influence, the partial correlation reflects the correlation between the dependent and independent variables.

Assume $x_{i(\min,tml,\max)}$ and $y_{i(\min,tml,\max)}$ is a vector with the minimum value, the most likely value and the maximum value of i_{th} variable x and y, respectively. And then the correlation coefficient r_{xy} is calculated as the following equation:

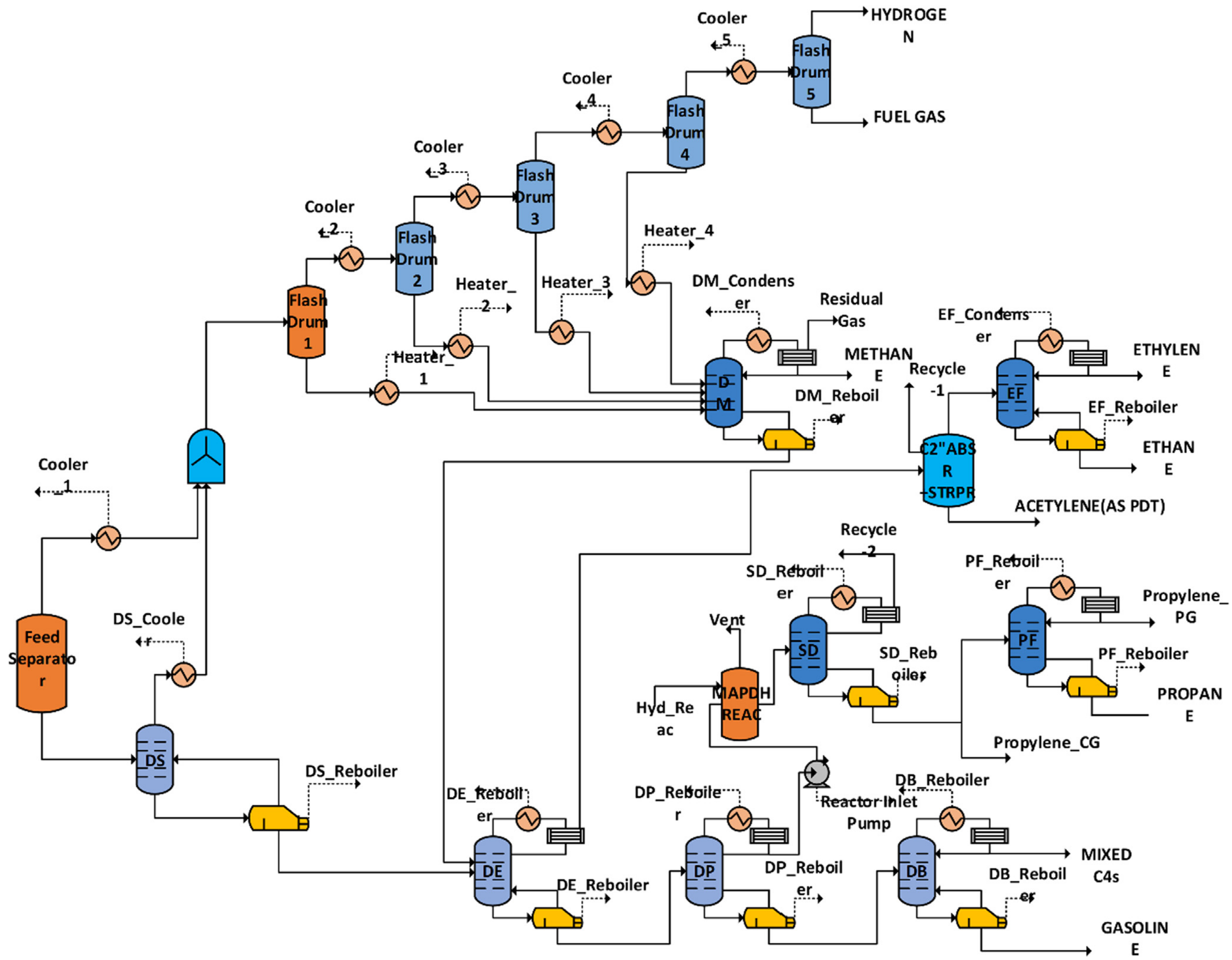

Fig. 3. A typical flowsheet of the ethylene plant.

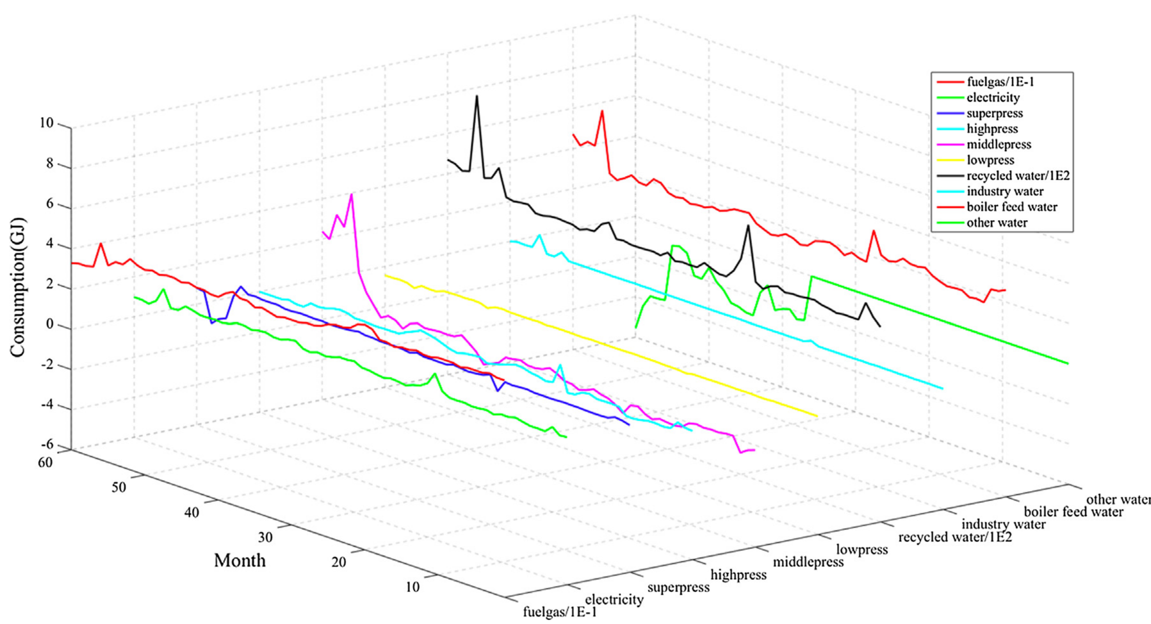

Fig. 4. The raw data of water, fuel, steam and electricity.

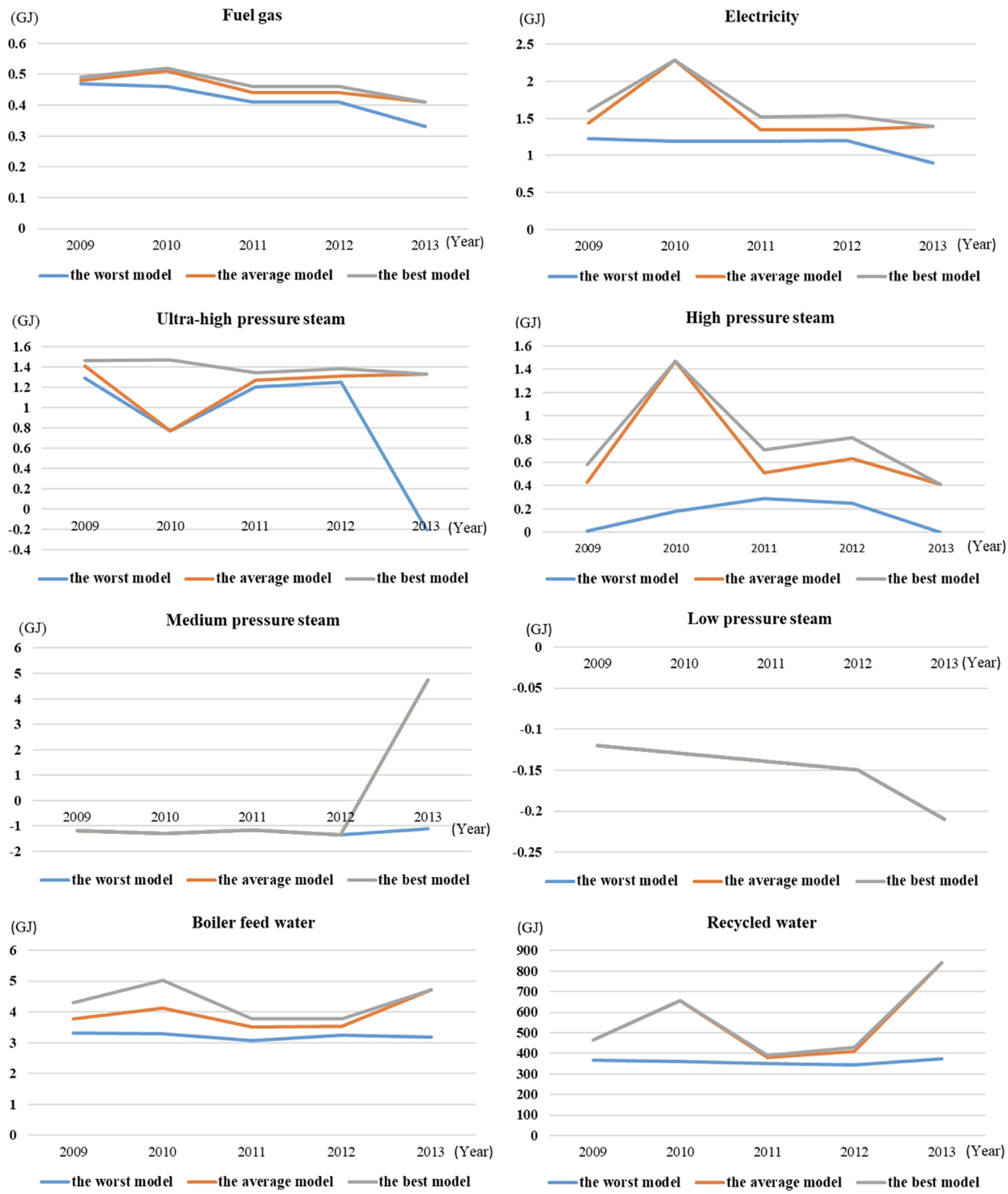

Fig. 5. The data of fuzzification of fuel gas, steam, water and electricity.

$$r_{xy(\min,tml,\max)} = \frac{\sum_{i=1}^{k}(x_{i(\min,tml,\max)} - \overline{x_{i(\min,tml,\max)}})(y_{i(\min,tml,\max)} - \overline{y_{i(\min,tml,\max)}})}{\sqrt{(x_{i(\min,tml,\max)} - \overline{x_{i(\min,tml,\max)}})^2}\sqrt{(y_{i(\min,tml,\max)} - \overline{y_{i(\min,tml,\max)}})^2}} \quad (9)$$

$\overline{x_{i(\min,tml,\max)}}$, $\overline{y_{i(\min,tml,\max)}}$ express the mean value of variable $x_{i(\min,tml,\max)}$ and $y_{i(\min,tml,\max)}$, respectively. And k is the total number of elements that contained in variable x and y.

And then the correlation coefficients matrix R is obtained.

$$R_{(\min,tml,\max)} = \begin{pmatrix} r_{11(\min,tml,\max)} & \cdots & r_{1n(\min,tml,\max)} \\ \vdots & \ddots & \vdots \\ r_{n1(\min,tml,\max)} & \cdots & r_{nn(\min,tml,\max)} \end{pmatrix}_{n*n} \quad (10)$$

In order to get the partial correlation coefficient matrix, the inverse matrix I of the correlation coefficient matrix R is obtained in Eq. (11).

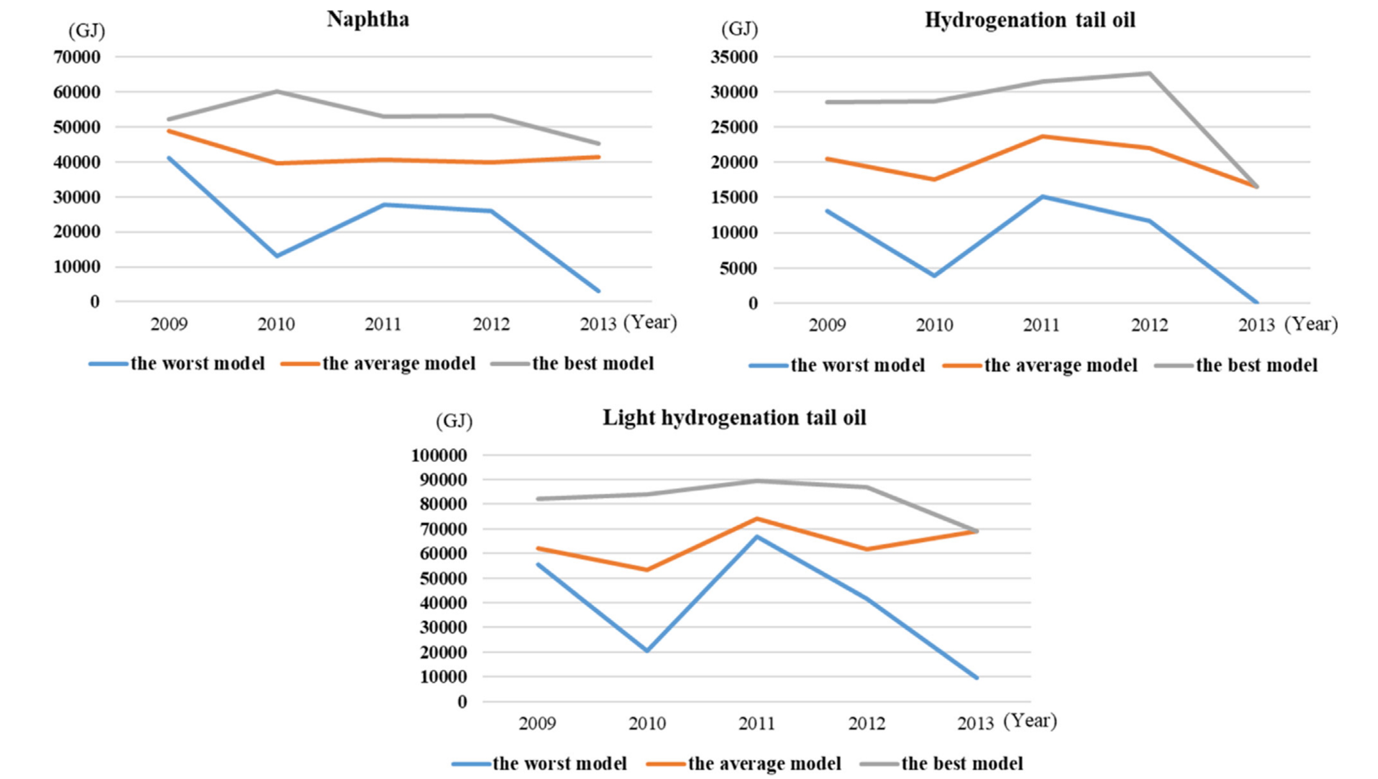

Fig. 6. The data of fuzzification of crude oils.

Table 1
The partial correlation matrix of minimum value.

	LDL	NAP	RAF	HDL	LHY	C345	OTH	FG	SP	HP	MP	LP	RW	IW	BW	OW	E
LDL	−1.00	0.09	0.15	−0.21	−0.31	0.08	−0.11	−0.04	0.41	−0.02	0.18	0.12	0.21	−0.03	0.23	0.16	−0.06
NAP	0.09	−1.00	0.30	0.33	−0.01	−0.31	0.52	0.11	0.03	−0.08	0.00	−0.22	0.14	−0.06	0.21	0.23	−0.27
RAF	0.15	0.30	−1.00	0.08	−0.04	0.09	−0.02	−0.03	−0.19	0.00	−0.04	0.05	−0.33	0.11	−0.27	−0.22	0.29
HDL	−0.21	0.33	0.08	−1.00	0.04	0.58	−0.32	−0.06	−0.08	−0.16	−0.03	0.19	0.00	0.06	−0.08	−0.09	−0.23
LHY	−0.31	−0.01	−0.04	0.04	−1.00	0.04	0.00	0.03	0.24	0.02	0.11	0.05	0.00	−0.10	0.16	0.13	−0.05
C345	0.08	−0.31	0.09	0.58	0.04	−1.00	0.08	0.06	−0.05	−0.13	−0.04	−0.11	0.02	−0.09	−0.11	−0.07	0.16
OTH	−0.11	0.52	−0.02	−0.32	0.00	0.08	−1.00	−0.04	−0.18	−0.25	0.06	0.13	−0.13	−0.09	−0.38	−0.40	0.23
FG	−0.04	0.11	−0.03	−0.06	0.03	0.06	−0.04	−1.00	−0.03	0.03	−0.35	0.06	0.13	0.19	0.15	0.24	0.02
SP	0.41	0.03	−0.19	−0.08	0.24	−0.05	−0.18	−0.03	−1.00	−0.67	−0.43	0.04	−0.11	0.53	−0.36	−0.44	−0.06
HP	−0.02	−0.08	0.00	−0.16	0.02	−0.13	−0.25	0.03	−0.67	−1.00	−0.15	0.05	−0.17	0.33	−0.35	−0.43	0.05
MP	0.18	0.00	−0.04	−0.03	0.11	−0.04	0.06	−0.35	−0.43	−0.15	−1.00	0.18	0.18	0.58	0.03	0.19	−0.20
LP	0.12	−0.22	0.05	0.19	0.05	−0.11	0.13	0.06	0.04	0.05	0.18	−1.00	−0.03	−0.15	−0.07	−0.05	0.08
RW	0.21	0.14	−0.33	0.00	0.00	0.02	−0.13	0.13	−0.11	−0.17	0.18	−0.03	−1.00	−0.17	−0.17	−0.38	0.26
IW	−0.03	−0.06	0.11	0.06	−0.10	−0.09	−0.09	0.19	0.53	0.33	0.58	−0.15	−0.17	−1.00	−0.11	−0.23	0.31
BW	0.23	0.21	−0.27	−0.08	0.16	−0.11	−0.38	0.15	−0.36	−0.35	0.03	−0.07	−0.17	−0.11	−1.00	−0.68	0.32
OW	0.16	0.23	−0.22	−0.09	0.13	−0.07	−0.40	0.24	−0.44	−0.43	0.19	−0.05	−0.38	−0.23	−0.68	−1.00	0.34
E	−0.06	−0.27	0.29	−0.23	−0.05	0.16	0.23	0.02	−0.06	0.05	−0.20	0.08	0.26	0.31	0.32	0.34	−1.00

Table 2
The correlation grade.

	[−1 −0.6]	(−0.6 0.3]	(−0.3 0.3)	[0.3 0.6)	[0.6 1]
Correlation	Strong-correlated	Weak-correlated	Non-correlated	Weak-correlated	Strong-correlated

$$I_{(\min,tml,\max)} = \mathrm{inv}(R_{(\min,tml,\max)}) = \begin{pmatrix} i_{11(\min,tml,\max)} & \cdots & i_{1n(\min,tml,\max)} \\ \vdots & \ddots & \vdots \\ i_{n1(\min,tml,\max)} & \cdots & i_{nn(\min,tml,\max)} \end{pmatrix}_{n*n} \quad (11)$$

And then the partial correlation coefficient $p_{ij(\min,tml,\max)}$ can be calculated based on Eq. (12) as the following:

$$p_{ij(\min,tml,\max)} = \frac{i_{ij(\min,tml,\max)}}{\sqrt{|i_{ii(\min,tml,\max)} * i_{jj(\min,tml,\max)}|}} \quad (12)$$

3.2.2. Modeling the FISM

According to the partial correlation coefficient, the adjacency relation between two variables can be obtained. If the absolute value of $p_{ij(\min,tml,\max)}$ is greater than the threshold, $a_{ij(min,tml,max)} = 1$ and $a_{ij(min,tml,max)} = 0$, or else$a_{ij(min,tml,max)} = 0$ and$a_{ji(min,tml,max)} = 1$. And then the adjacency relation matrix A is shown in the following:

$$A_{(\min,tml,\max)} = \begin{pmatrix} a_{11(\min,tml,\max)} & \cdots & a_{1n(\min,tml,\max)} \\ \vdots & \ddots & \vdots \\ a_{n1(\min,tml,\max)} & \cdots & a_{nn(\min,tml,\max)} \end{pmatrix}_{n*n} \quad (13)$$

And an n order identity matrix E is shown in Eq. (14).

Table 3
The reachability matrix of minimum values.

	LDL	NAP	RAF	HDL	LHY	C345	OTH	FG	SP	HP	MP	LP	RW	IW	BW	OW	E
LDL	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1
NAP	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
RAF	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HDL	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
LHY	1	0	0	0	1	0	0	0	1	0	0	0	0	1	0	0	1
C345	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
OTH	0	1	1	1	0	1	1	0	0	0	0	0	0	0	0	0	0
FG	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0
SP	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	1
HP	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	1
MP	0	0	0	0	0	0	0	1	1	0	1	0	0	1	0	0	1
LP	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
RW	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0
IW	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
BW	0	1	1	1	0	1	1	0	1	1	0	0	0	1	1	0	1
OW	0	1	1	1	0	1	1	0	1	1	0	0	1	1	1	1	1
E	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 4
The ISM model of the energy consumption data.

Variables	Reachable sets (P)	First set (Q)	Intersection (S)
LDL	LDL, SP, IW, E	LDL, LHY	LDL
NAP	NAP, RAF, HDL, C345, OTH	NAP, HDL, C345, OTH, BW, OW	NAP, HDL, C345, OTH
RAF	RAF	NAP, RAF, HDL, C345, OTH, RW, BW, OW	RAF
HDL	NAP, RAF, HDL, C345, OTH	NAP, HDL, C345, OTH, BW, OW	NAP, HDL, C345, OTH
LHY	LDL, LHY, SP, IW, E	LHY	LHY
C345	NAP, RAF, HDL, C345, OTH	NAP, HDL, C345, OTH, BW, OW	NAP, HDL, C345, OTH
OTH	NAP, RAF, HDL, C345, OTH	NAP, HDL, C345, OTH, BW, OW	NAP, HDL, C345, OTH
FG	FG	FG, MP	FG
SP	SP, IW, E	LDL, LHY, SP, HP, MP, BW, OW	SP
HP	SP, HP, IW, E	HP, BW, OW	MP
MP	FG, SP, MP, IW, E	MP	MP
LP	LP	LP	LP
RW	RAF, RW	RW, OW	RW
IW	IW, E	LDL, LHY, SP, HP, MP, IW, BW, OW	IW
BW	NAP, RAF, HDL, C345, OTH, SP, HP, IW, BW, E	BW	BW
OW	NAP, RAF, C345, OTH, SP, HP, RW, IW, BW, OW, E	OW	OW
E	E	E	E

$$E = \begin{pmatrix} (111) & \dots & (000) \\ \vdots & \ddots & \vdots \\ (000) & \cdots & (111) \end{pmatrix}_{n*n} \quad (14)$$

If

$$A_{(\min,tml,\max)} + E = (A_{(\min,tml,\max)} + E)^2 = (A_{(\min,tml,\max)} + E)^3 = \dots = (A_{(\min,tml,\max)} + E)^{k-1} = (A_{(\min,tml,\max)} + E)^k \quad (15)$$

Then $D_{(\min,tml,\max)} = (A_{(\min,tml,\max)} + E)^{k-1}$ is called the reachability matrix of A.

$$D_{(\min,tml,\max)} = \begin{pmatrix} d_{11(\min,tml,\max)} & \dots & d_{1n(\min,tml,\max)} \\ \vdots & \ddots & \vdots \\ d_{n1(\min,tml,\max)} & \cdots & d_{nn(\min,tml,\max)} \end{pmatrix}_{n*n} \quad (16)$$

Definition 1. V is a set which contains n variables. v_i and v_j are the i_{th}(j ≤ n) variable and the j_{th}(j ≤ n) variable, respectively. If$d_{ij(\min,tml,\max)} = 1$, then the variable v_j is added into $P_{i(\min,tml,\max)}$ and v_i is added into$Q_{j(\min,tml,\max)}$. $P_{i(\min,tml,\max)}$ is called the reachable set of v_i and $Q_{j(\min,ml,\max)}$ is called of first set of v_j.

$S_{i(\min,tml,\max)}$ is the intersection of $P_{i(\min,tml,\max)}$ and $Q_{i(\min,tml,\max)}$. If $S_{i(\min,tml,\max)} = P_{i(\min,tml,\max)}$, the i_{th} variable is the top-level variable. And then remove all the i_{th} variable from $P_{i(\min,tml,\max)}$ and $Q_{j(\min.tml,\max)}$. Look for the sub top-level variable with the relation $S_{i(\min,tml,\max)} = P_{i(\min,tml,\max)}$. Repeat this action until all variables are layered.

3.3. The structure analysis based on the FISM

The structure analysis framework based on the FISM method is described as the following:

Step 1: Select the input data, and carry on triangular fuzzification based on Eqs. (6)–(8).
Step 2: Build the correlation coefficients matrix r based on Eqs. (9) and (10).
Step 3: Establish the partial correlation coefficients matrix using the inverse matrix of r based on Eqs. (11) and (12).
Step 4: Transform the adjacency matrix A by Eqs. (13)–(16), which is made of correlation coefficient thresholds, to the reachability matrix R.
Step 5: The elements of each level can be obtained by using the FISM.

The flow chart of the FISM is shown in Fig. 2.

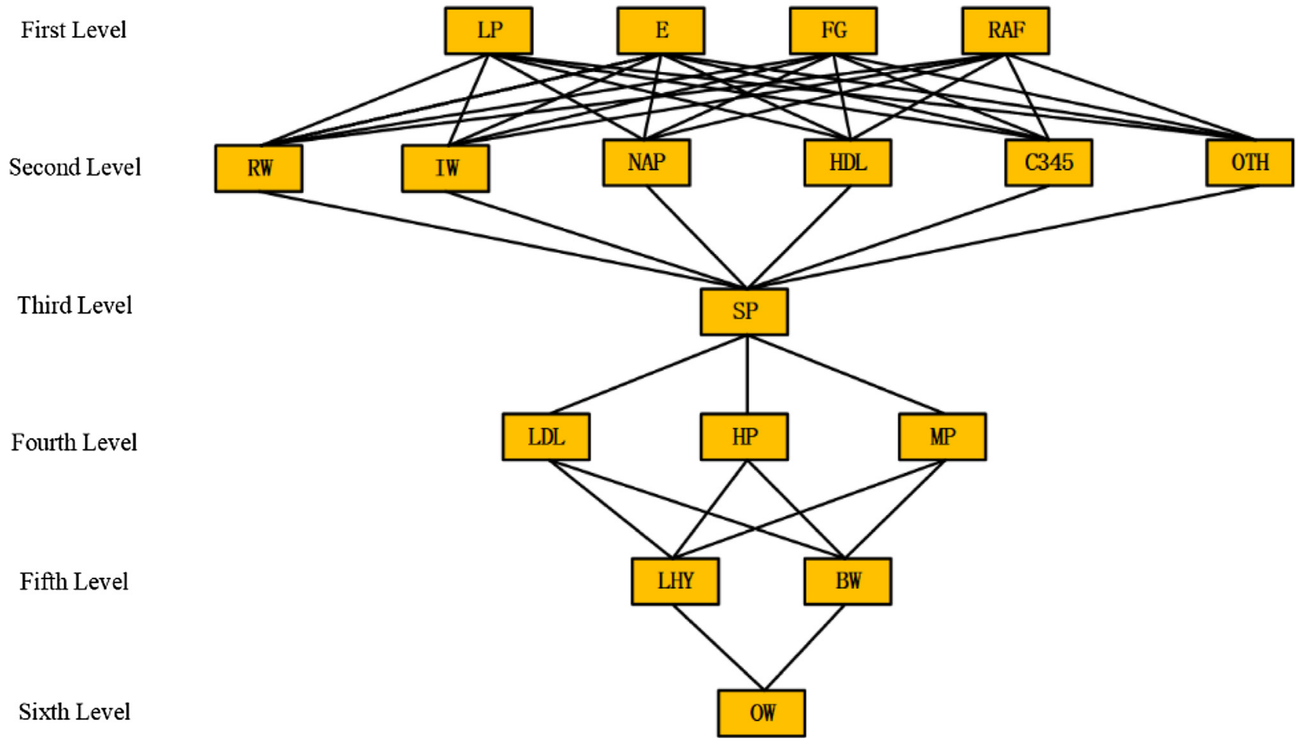

Fig. 7. The energy structure of the worst model.

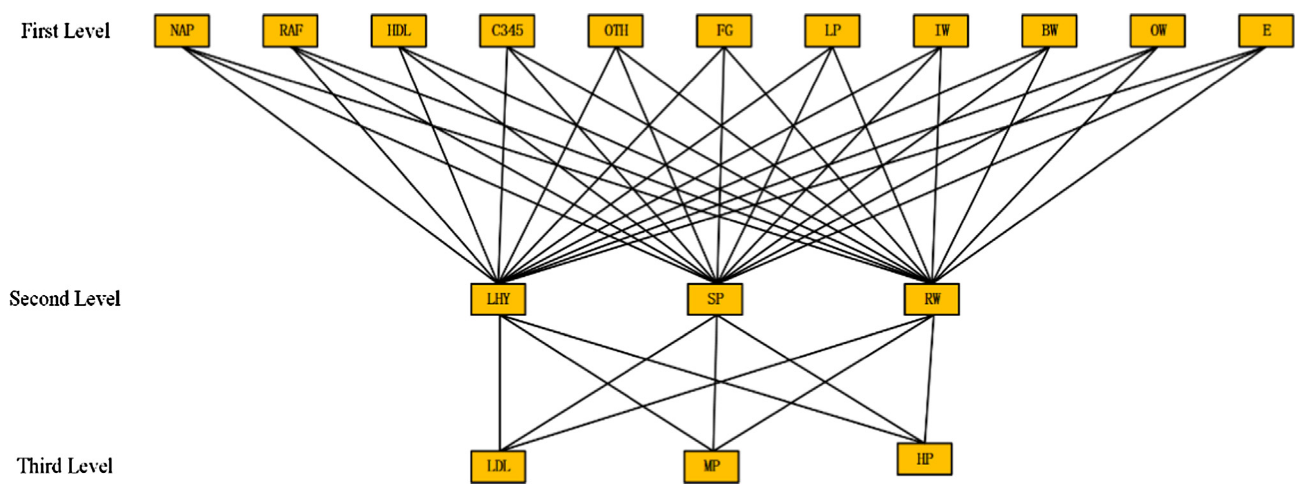

Fig. 8. The energy structure of the average model.

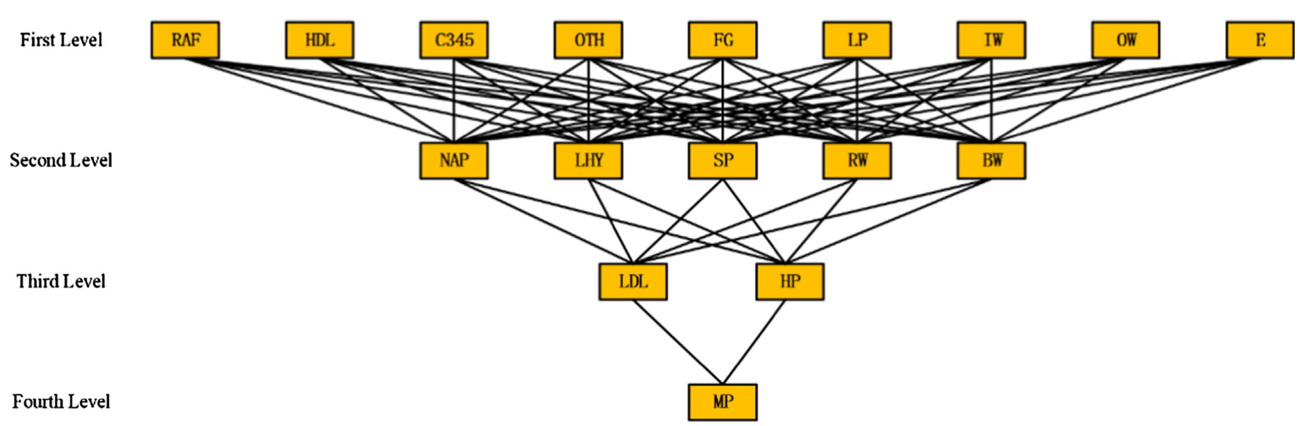

Fig. 9. The energy structure of the best model.

Table 5
Common carbon dioxide emission (Unit: Ton CO_2/Ton).

Energy	Carbon dioxide emission	Energy	Carbon dioxide emission
Raw coal	2.07	kerosene	3.08
Cleaned coal	2.49	Diesel	3.16
Slime, middlings	0.89	Refinery dry gas	2.65
Briquette	2.02	Liquefied petroleum gas	3.17
Coal briquette total	2.23	OTH coke products	3.04
Coke	3.04	OTH petroleum products	2.95
Crude oil	3.07	Natural gas	21.84
Fuel oil	3.24	Coke oven gas	7.71
Gasoline	3	OTH coal gas	5.92

4. Case study: Energy structure analysis and energy saving of the ethylene production industry

4.1. Ethylene production plants

There are about seven kinds of process technologies in Chinese ethylene product industries [25]. According to the statistics, the energy consumption fees are up to more than 50% of total cost for ethylene product process and more than 70% of the total cost in ethylene production is taken by cracking materials (Naphtha, light diesel oil, raffinate, hydrogenation tail oil, carbon3, carbon4, carbon5 and other materials) [25].

In ethylene production plants, cracking and separation are the core processes. In order to ensure the normal running of cracking furnace, a large number of fuels as mentioned above need to provide much heat to the tube cracking reactions and a Transfer Line Exchanger (TLE) produces a great amount of steam by recycling excess heat. In addition, for the sake of making the raw material hydrocarbon finish the ideal cleavage reactions in a short time and reducing the use of coke at the same time, the steam should be injected when the hydrocarbon is poured into the cracking furnace. In separation phase, there normally contains three parts: a rapid cooling, a compression and a separation part. The typical flowsheet of the ethylene plant is described in detail as shown in Fig. 3.

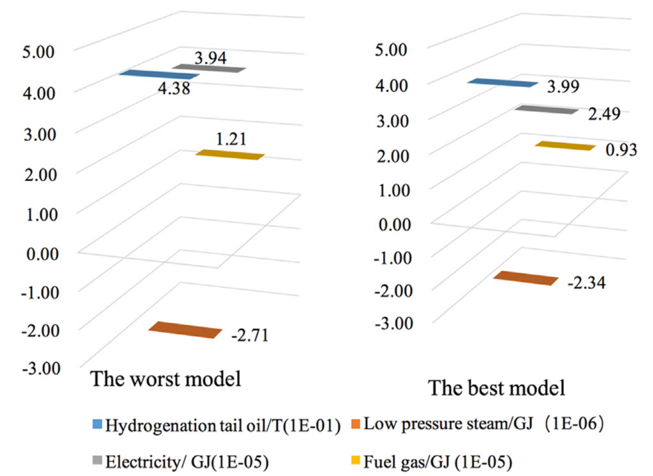

Fig. 11. The comparisons of main factors in the worse model and the best model.

4.2. Data preprocess

Based on the factor analysis of energy consumption in the ethylene plant, 17 main raw materials data of several areas from 2009 to 2013 are obtained [25]. These 17 kinds of raw materials include several kinds of crude oils (Naphtha (NAP), light diesel oil (LDL), Raffinate (RAF), hydrogenation tail oil (HDL), light hydrogenation tail oil (LHY), carbon3, carbon4, carbon5 (C345) and other force (OTH)), fuels (fuel gas (FG), light oil and heavy oil, where FG is selected as the main fuel because of the little effects of light oil and heavy oil), steam (ultra-high pressure steam (SP), high pressure steam (HP), medium pressure steam (MP), low pressure steam (LP)), water (recycled water (RW), industrial water (IW), boiler feed water (BW), other water (OW)), electricity (E). These 17 raw materials serve as the inputs, and the ethylene production is taken as the output.

For the sake of uniform calculation, the consumptions of fuel, electricity, water, and steam are generally converted to the amount in unit of GJ [38] based on the standard SH/T3110-2001 [39], DB 37/751-2007 [40] and GB/T 2589-2008 [41], while the feed, ethylene production are converted to the amount in unit of Ton. Based on the standard above, the raw data of water, fuel, steam and electricity in one

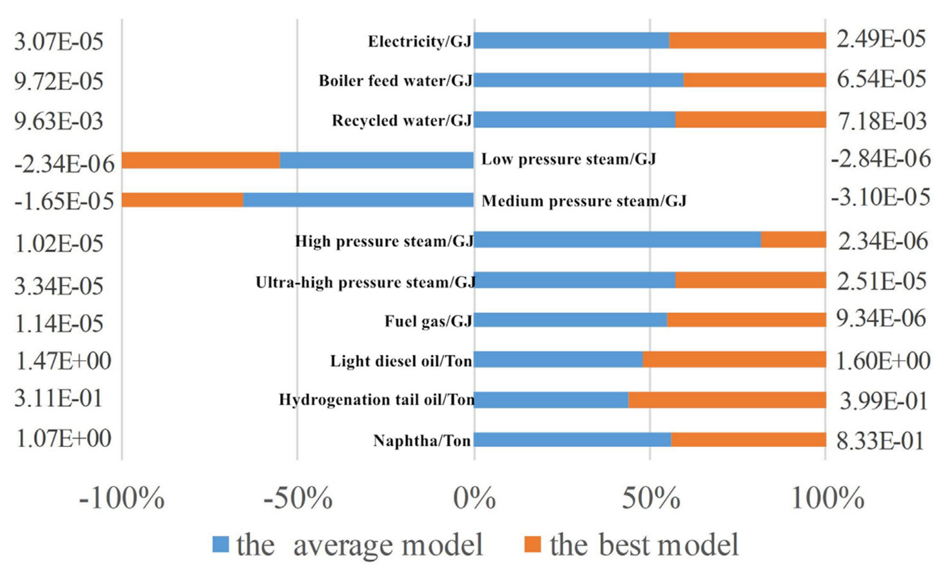

Fig. 10. The raw material consumptions per Ton ethylene.

ethylene production plant is shown in Fig. 4. Meanwhile, in the experiment, MATLAB is used as the computational software, which is widely used in scientific research, data processing and mathematical modeling [42].

4.3. Energy structure analysis and energy saving

In order to find the characteristic values of the statistical data in a year and dispose the external interference, the monthly data are divided into the upper limit, lower limit and the most probable value based on Eqs. (1)–(8). The fuzzification results with the minimum, the most likely and the maximum TFNs of the selected plant from 2009 to 2013 are shown in Figs. 5 and 6. Wherein the grey line represents the best result, the red line represents the average result and the blue line represents the worst result. The average result of the fuel gas, the high pressure steam, the electricity and the recycled water is closed to the best result, so the improvement potential of these input factors is low. And the three lines is the same in the low pressure steam, so the improvement potential of the low pressure steam is lower. On the contrary, crude oils have greatest improvement potential. And the fuzzy results of the other plants can be obtained in the same way.

Based on the TFN calculated above and Eqs. (13) and (14), correlation coefficients can be calculated in the minimum production configurations. The partial correlation matrix in the minimum production configurations is shown in Table 1.

In order to get an adjacency relation matrix, a proper threshold is needed to be selected. Based on this correlation grade described in Table 2, the threshold of the correlation is set as 0.3 in this paper. If $|p_{ij}| \geqslant 0.3$, then set $a_{ij} = 1$ and $a_{ji} = 0$. And if $|r_{ij}| < 0.3$, then set $a_{ij} = 0$ and $a_{ji} = 1$. The first reachability matrix is shown in Table 3.

It can be seen from Table 3 that light diesel oil has a direct impact on ultra-high pressure steam, industrial water and electricity. Naphtha has a direct impact on raffinate, hydrogenation tail oil, C345 and other force. Meanwhile, C345 and other force impact each other. In addition, C345 and other force have a direct impact on naphtha, raffinate, hydrogenation tail oil etc. The reachable set $P_{i\,\min}$, the first set $Q_{j\,\min}$ and their intersection $S_{i\,\min}$ in the first layer can be obtained by the reachability matrix $D_{(\min,tml,\max)}$ as shown in Table 4. And the other layers can be obtained in the same way.

Based on different reachable sets and first sets, the energy structure of the minimum production configurations (the worst model) can be built by using the ISM as shown in Fig. 7. Similarly, the energy structure of the most likely production configurations (the average model) and the maximum production configurations (the best model) is shown in Figs. 8 and 9, respectively.

It can be seen from Figs. 7–9 that the top layer impact factors in different situation are distinct. In the energy structure of the worst model, low pressure steam, electricity, fuel gas and raffinate are the main factors. And light oil and heavy oil, medium pressure steam and high pressure steam have little influence in the energy structure of the average model. However, raffinate, hydrogenation tail oil, C345, other force, fuel gas, low pressure steam, industrial water, other water and electricity are the main factors in the best model. And the middle pressure steam has the least impact than the other variables.

Based the key impact factors of influencing the ethylene production in different production configurations and the common carbon dioxide emission of all kinds of raw materials as shown in Table 5 [37], the raw materials consumption and the carbon emission can be reduced.

The ethylene yields of the average model and the best model of the plant in 2012 are 39,496 Tons and 53,190 Tons [35], respectively. And the raw material consumptions per Ton ethylene in the average model and the best model are shown in Fig. 10.

It can be seen from Fig. 10 and Table 5 that compared with the benchmarking of the best production configuration, the naphtha and the boiler water are the key factors of the average model. Therefore, if the inputs reduce 2.37E-01 Ton naphtha and 3.18E-05 GJ boiler water when producing one Ton ethylene, then the target of reduce energy consumption can be achieved. Meanwhile, the carbon emission can be reduced about 0.325 Ton when the ethylene is produced about one Ton.

Similarly, the adjustment direction of the worst model can be obtained as shown in Fig. 11 based on the production configurations in the worst model and the best model.

It can be seen from Fig. 11 and Table 5 that compared with the benchmarking of the best production configuration, the adjustment of production parameters can be obtained. If the inputs reduce 1.45E-01 Ton hydrogenation tail oil when producing one Ton ethylene, then the carbon emission can be reduced about 0.44 Ton. Meanwhile, the energy efficiency of the worse model can achieve the effective level.

5. Discussion

First, a novel FISM based on data fuzzification is proposed. The statistical data including the uncertain data can be divided into maximum, minimum and the most likely situations by using the data fuzzification method. And then the structured analyses of different production status affecting the energy saving and carbon emission are obtained by the FISM.

Second, this proposed method is applied in energy structured analysis and energy saving of the complex ethylene industry. And three energy structural models with the worst model, average model and the best model under different production status can be obtained. Based on the optimal production allocation, we can find out the key impact factors which affect the energy efficiency and carbon emissions. Moreover, by adjusting the production configuration of the worst model and the average model, the raw materials can be saved from 10% to 30% and the carbon emission can be reduced about 0.288 Ton when every Ton of ethylene is produced.

Third, the proposed model still has some drawbacks. The threshold of the FISM is determined based on the practical experience. Therefore, we will use the self-adaption artificial neural network method to optimize the threshold of the FISM in complex chemical industries

6. Conclusion

This paper proposes an energy structure analysis and energy saving method based on the FISM. The uncertain data can be disposed based on the data fuzzification method. And then the main factors and the energy structure of different production status are analyzed by the proposed method. Moreover, this proposed method is applied in energy structured analysis and energy saving of complex chemical industries. The main factors that affect the energy efficiency of the ethylene product systems in complex chemical industries can be objectively analyzed by using the FISM. Furthermore, compared with different production status, the experimental results show the proposed method can save the raw materials from 10% to 30% and reduce the carbon emission about 0.288 Ton when every Ton of ethylene is produced.

In our further works, the pollutant emissions should be taken into account. Meanwhile, we will integrate some artificial intelligence methods, such as particle swarm optimization, deep learning, to adaptively adjust the threshold of the FISM. Furthermore, we will analyze the energy efficiency and the carbon emission by combining the mechanism model and the data-driven model only from a mathematical perspective.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.applthermaleng.2018.07.030.

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