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Energy optimization and analysis modeling based on extreme learning machine integrated index decomposition analysis: Application to complex chemical processes

Zhiqiang Geng [a, b], Xiao Yang [a, b], Yongming Han [a, b, *], Qunxiong Zhu [a, b, **]

[a] College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China
[b] Engineering Research Center of Intelligent PSE, Ministry of Education of China, Beijing 100029, China

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ABSTRACT

Energy optimization and analysis of complex chemical processes play a significant role in the sustainable development procedure. In order to deal with the high-dimensional and noise data in complex chemical processes, we present an energy optimization and analysis method based on extreme learning machine integrating the index decomposition analysis. First, index decomposition analysis has been used to decompose the high-dimensional data to three energy performance indexes of the activity effect, the structure effect and the intensity. And then, those indexes and the production/conductivity of the chemical process are defined as inputs and outputs of the extreme learning machine respectively to build energy optimization and analysis model. Finally, the proposed method has been applied to optimizing and analyzing energy status of the ethylene system and the purified terephthalic acid solvent system in complex chemical processes. The experiment results show that the proposed method has the characteristics of fast learning, stable network outputs and high model accuracy in handling with the high-dimensional data. Moreover, it can optimize energy of chemical processes and guide the production operation. In our experiment, the production of ethylene plants can be increased by 5.33%, and the conductivity of purified terephthalic acid plants can be reduced by 0.046%.

1. Introduction

Complex chemical processes make a difference in developing the industry development in China. At the same time, the ethylene production is the main process in chemical industries. However, the energy efficiency level of ethylene production is far lower than the international advanced level in the chemical industry [1,2]. More than 50% of the ethylene plants operating costs are derived from the cost of energy consumption of ethylene [3]. Meanwhile, the demand of PTA (purified terephthalic acid) has increased in recent years and has become a significant row material in chemical industries. Unfortunately, On account of the high cost of adding a new plant, the overall energy efficiency has decreased [4]. In summary, it is an effective way to improve the productivity and energy efficiency of the complex chemical process by building the energy optimization and analysis model.

Although the optimal index method and the mean method are commonly used to analyze the energy efficiency [5], the energy-saving knowledge cannot be applied to guide the analysis of actual situation of energy efficiency. Data fusion method is much better to analyze the energy efficiency of ethylene plants. Geng et al. proposed an extraction method based on data fusion for the ethylene industry [6], and the hierarchical linear optimal fusion algorithm has been used for energy consumption indices acquisition [7]. But they do not take into account the impact factors of energy consumption indicators. Kleemann et al. optimize the recovering method to save the energy in chemical processes [8]. However, it does not take the economic cost of restructuring the industrial plants into consideration. Geng et al. analyzed the performance efficiency of China's ethylene plats by using the Data Envelopment Analysis (DEA) integrated Analytic Hierarchy Process (AHP) [9] and DEA-cross model [10]. Han et al. based on fuzzy DEA cross-model proposed a method to analysis the energy efficiency

* Corresponding author. College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China.
** Corresponding author. College of Information Science and Technology, Beijing University of Chemical Technology, Beijing 100029, China.
E-mail addresses: hanym@mail.buct.edu.cn (Y. Han), zhuqx@mail.buct.edu.cn (Q. Zhu).

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[11]. However, the efficiency discrimination of DEA will be poor when more than a third of efficiency values are set to 1 [12]. Olanrewaju et al. integrated IDA-ANN-DEA to evaluate and optimize energy consumption in industrial sectors [13] and to assess the energy potential in the South African industry [14] while they did not take into account the local minimization problem, convergence rate and the structure of traditional ANN. And this method is used to assess broad industry, but not instance to the specific production process and offer a guidance of that process. The existing energy optimization and analysis methods in the complex chemical processes are insufficient. Therefore, we propose an extreme learning machine (ELM) based on index decomposition analysis (IDA) (IDA-ELM) method to optimize and analyze the energy of the chemical industry. In our experiment, the production of ethylene plants can be increased by 5.33%, and the conductivity of PTA plants can be reduced by 0.046%.

Our remainder study is elaborated as the following manner. Section 2 introduces the current research status of energy analysis and optimizes in chemical processes with ELM and IDA. The ELM and the IDA have been explained in detail and the energy optimization and analysis model based on IDA-ELM in the complex chemical process is also illustrated in Section 3. Section 4 presents the case study about energy optimization and analysis of ethylene production industry and PTA production industry based on IDA-ELM, respectively. Finally, the conclusions are obtained in Section 5.

2. Related work

Generally, in order to build the energy optimization and analysis model of the complex chemical process, we need to consider the following characteristics: easy to be disturbed by external interference, high dimension, noise, and varied. Many artificial intelligence methods can be used to deal with this problem, such as genetic algorithm, bird-mating [15] and artificial neural network (ANN) [16]. Among them the most primary characteristic of the ANN are paralleled distributive processing, continuous time-related nonlinear dynamics, and fast response without considering the internal mechanism, so it is widely used in many fields: Hong et al. use ANN and an improved Particle Swarm Optimization to explain the PV system performance [17]. Certainly, ANN has also been commonly used in modeling complex chemical processes [18]. Geng et al. proposed an energy efficiency predict method based on neural network [19]. Li et al. used artificial network to simulate the gas generation and transport [20], and Barrasso et al. descript the wet granulation process by the artificial network [21]. However, the neural network learning algorithms are easy to fall into local minimum and slow convergence. The ELM is a single hidden layer feed-forward neural network proposed by Huang et al. [22]. The ELM uses Moore-Penrose generalized inverse to calculate the weight in the output layer instead of changing the weight during training, which has been used in the traditional way [23]. Therefore, the ELM avoids the tedious training and a variety of problems produced by the descent learning and the number of hidden nodes is the only parameter that needed to be defined. Meanwhile, the ELM has the characteristics of good performance in generalization and fast convergence speed. Therefore, ELM has been widely used in classification like spectroscopy-based classification with ELM in food industry [24] and classification applications to votes [25], building the batch process model [26], Soft-sensing model development [27], applying bulk polymerization of the styrene batch process and evaluate control actions [28], wind speed forecasting etc. [29]. He et al. proposed a double parallel structure ELM and used the Pearson Correlation Coefficient (PCC) between the output and input to build two independent subnets. This method was proposed to accurately model and develop a data driven soft sensor for complex chemical processes [30]. Suresh et al. presents a real-coded genetic algorithm to select the optimal number of hidden neurons, input weights and bias. This method also presents an alternate and less computationally intensive approach to search the best parameters of ELM, which improve the ELM performance in sparse multi-category classification problems [31]. Salcedo-Sanz., et al. combine the modified Harmony Search optimization algorithm with ELM to select the best set of features for ELM and predict the one-year-ahead energy demand [32]. Liu et al. use four signal decomposing algorithms to combine four different hybrid models and calculate the input of ELM, so that all the hybrid algorithms have better performance in wind speed forecasting [33]. He et al. proposed a data-attribute-space-oriented double parallel structure to enhance the ELM machine and applicate it to the regression datasets [34]. However, the ELM has a problem with the validity of analysis in complex chemical processes. An IDA is exploited to select the main index among input variable to improve the reliability and the analysis accuracy.

During the practical analysis, the production of complex chemical processes is always affected by many parameters. And the parameters are easily disturbed by the outside. Each parameter has a certain amount of information. In addition, there is mutual influence among parameters. Because of the complexity in the complex chemical processes, there are some errors and noises in the parameters during the measurement.

IDA is a promising method for analyzing energy efficiency [35]. IDA methodology has been divided into additive and multiplicative [36], and has been widely used in energy and carbon emission analyses [37]. What's more, various studies have contributed to the use of the IDA [38], for example, Unander et al. use this method to decompose the IEA countries' energy-use [39]. In Brazil, IDA has been used to decompose the energy use [40]. Hatzigeorgiou et al. decomposed the CO_2 emissions in Greece during 1990–2002 into four factors: energy intensity effect, income effect, population effect fuel and share effect by using the IDA, and obtained the result that the main element is the income effect [41]. Hammond et al. uses decomposition analysis to separate the contributions of changes into five parts to the reduction in carbon emissions. And the reduction in energy intensity is the primary reason [42]. The research results mentioned above show the effectiveness and practicality of the IDA. However, the IDA method is only combined with the indicators of each domain for energy efficiency analysis and evaluation, but did not give the corresponding improvement and the specific improvement direction. Therefore, we propose IDA-ELM to analyze the production and energy consumption of ethylene plants and PTA plants.

Ethylene product system and PTA product system are typical examples of complex chemical processes. All of those systems have the characteristics of high-dimension and noise, thus IDA can be used to decompose these variables into several parts so that we can easily utilize accessible operational data to further obtain the crucial parameter and primary cause. Therefore, we can reduce the redundant features to shorten the analysis time and improve the accuracy. Meanwhile, the complex mechanism in those chemical processes can be avoided. The features of complex chemical processes data are extracted based on the IDA, which are set as the input of ELM. And then we let the production/conductivity of each plant to be the output data of ELM. Finally, comparing with the ELM, we use the IDA-ELM model to optimize and analyze energy status of ethylene system and the PTA solvent system to test the feasibility and effectiveness. Furthermore, it can also offer the operation guidance for energy saving.

3. IDA-ELM

In order to deal with the high-dimensional and noise data of the complex chemical processes, we introduce the IDA into the traditional ELM. Therefore, the IDA-ELM can reduce the dimensions, filter redundant information, decrease noise impact and build a more accurate energy efficiency analysis model in complex chemical processes.

3.1. Extreme learning machine

Suppose that training samples Y are represented as the following equation:

$$\mathrm{Y} = \left\{ (\boldsymbol{A}_y, \boldsymbol{B}_y) \middle| y = 1, 2, \ldots, \mathrm{Y}; \boldsymbol{A}_y \in \boldsymbol{R}^M; \boldsymbol{B}_y \in \boldsymbol{R}^N \right\} \tag{1}$$

So the ELM neural network which has the hidden nodes of Z can be expressed as:

$$\boldsymbol{B}_y = \aleph(\boldsymbol{A}_y) = \sum_{z=1}^{Z} \boldsymbol{\gamma}_z g(\boldsymbol{\alpha}_z \cdot \boldsymbol{A}_y + \boldsymbol{t}_z) \tag{2}$$

Where$g(x)$ is the activation function, $\boldsymbol{\alpha}_z = [\alpha_{z1}, \alpha_{z2}, \ldots, \alpha_{zM}]$ are the weight between the zth hidden layer node and the mth input layer node and $\boldsymbol{\gamma}_z = [\gamma_{z1}, \gamma_{z2}, \ldots, \gamma_{zN}]$ are the weight between the zth hidden layer node and the nth output layer node. Where $\boldsymbol{t}_z$ is the threshold of the zth node and $\boldsymbol{\alpha}_z \cdot \boldsymbol{A}_y$ is the inner product between $\boldsymbol{\alpha}_z$ and $\boldsymbol{A}_y$.

In the algorithm theory of ELM, there are some values of $\boldsymbol{\gamma}_z$、 $\boldsymbol{\alpha}_z$ and$\boldsymbol{t}_z$ that makes the network can approach the expectation of $\boldsymbol{B}_y$ at the error of zero. Thus, Eq. (1) can be rewritten as the following equation:

$$\mathbf{H}\gamma = \mathbf{B} \tag{3}$$

where $\mathbf{H}$ is the output matrix of hidden layer:

$$\mathbf{H} = \begin{bmatrix} g(\boldsymbol{\alpha}_1 \cdot \boldsymbol{A}_1 + \boldsymbol{t}_1) & \cdots & g(\boldsymbol{\alpha}_Z \cdot \boldsymbol{A}_1 + \boldsymbol{t}_Z) \\ \vdots & \vdots & \vdots \\ g(\boldsymbol{\alpha}_1 \cdot \boldsymbol{A}_Y + \boldsymbol{t}_1) & \cdots & g(\boldsymbol{\alpha}_Z \cdot \boldsymbol{A}_Y + \boldsymbol{t}_Z) \end{bmatrix}_{Y \times Z} \tag{4}$$

So the weight vector $\boldsymbol{\gamma}$ between output layer and hidden layer can be calculated by the following equation:

$$\widehat{\boldsymbol{\gamma}} = \mathrm{H}^{+}\boldsymbol{B} \tag{5}$$

where $\boldsymbol{H}^{+}$ is the Moore-Penrose generalized inverse of $\boldsymbol{H}$.

In summary, ELM is calculated as follow:

(1) The weight $\boldsymbol{\alpha}_z$ between input layer and hidden layer and threshold are randomly generated, where$z = 1, 2, \ldots, Z$;
(2) Calculate the output matrix $\boldsymbol{H}$ of the hidden layer;
(3) Calculate the weight between output layer and hidden layer according to Eq. (4)

From all the above we can see that ELM do not need to learn the weight between hidden layer and output layer tediously, meanwhile, it also has a good generalization performance and convergence speed without providing the variety of parameters of the network. However, as complex process data consist of a large amount of high-dimensional data which are coupled and test variables always include inevitable error and noise data, ELM neural network that is used for complex process may lead to lower precision and bad performance of model.

3.2. Index decomposition analysis

IDA is an energy efficiency analysis method which is based on LMDI [43]. The IDA analyzes energy efficiency from three aspects: (1) energy savings; (2) the structure of energy efficiency; (3) energy performance indicators. The energy efficiency index of the IDA can assess the respective contributions of activity, structural and intensity effects. Thus, the IDA is the general specifications in energy efficiency and improving energy saving extent.

Suppose that U^N is the total energy consumption of m process units during the Nth time (day/month/year):

$$U^N = \sum_{i=1}^{m} Q^N \frac{Q_i^N}{Q^N} \frac{U_i^N}{Q_i^N} = \sum_{i=1}^{m} Q^N S^N I^N \tag{6}$$

where U^N is the total energy consumption of m process units at $\mathrm{N^{th}}$ time, Q^N is the total output of m process units at Nth time, that is the activity in LDMI. Q_i^N is the total product of ith process unit at Nth time, so $\frac{Q_i^N}{Q^N}$ is the activity ratio at the Nth time, that is the structural in LDMI. $\frac{U_i^N}{Q_i^N}$ is the energy consumption per unit of production, that is the energy intensity in LDMI.

If we suppose that $\Delta U_{act}^{0,N}$ is the changes in activity, $\Delta U_{\mathrm{str}}^{0,N}$ is the change in structure and $\Delta U_{\mathrm{int}}^{0,N}$ is the change in intensity. According to LMDI I, we get:

$$\Delta U^{0,N} = U^N - U^0 = \Delta U_{act}^{0,N} + \Delta U_{str}^{0,N} + \Delta U_{int}^{0,N} \tag{7}$$

$$\Delta U_{act}^{0,N} = \sum_{i=1}^{m} L\left(U_i^N, U_i^0\right) \ln \frac{Q^N}{Q^0} \tag{8}$$

$$\Delta U_{str}^{0,N} = \sum_{i=1}^{m} L\left(U_i^N, U_i^0\right) ln \frac{S^N}{S^0} \tag{9}$$

$$\Delta U_{int}^{0,N} = \sum_{i=1}^{m} L\left(U_i^N, U_i^0\right) ln \frac{I^N}{I^0} \tag{10}$$

where function L (x, y) is the geometric mean.

$$L(x, y) = \begin{cases} \dfrac{x - y}{\ln(x/y)}, & if\ x \neq y \\ 0, & if\ x = y \end{cases} \tag{11}$$

The energy consumption at reference timeU^0, productivity Q^0, activity ratio S^0, energy intensity I^0 are the average values of each variable at multiple time points over a period of time respectively.

3.3. The framework of energy analysis and optimizes based on the IDA-ELM

3.3.1. The IDA-ELM method

According to the algorithm we elaborated in 3.2, we can extract the features of the input data. And then we use those data to build an IDA-ELM neural network based on the modeling of high-dimensional data in complex chemical process system.

(1) Select the training sample sets. The training sample sets are the data from the complex chemical plants. Those data contains the related attributes of the plant. After the training of this data the ELM will learn some features of the plants.

Suppose that there are L training sample sets that contain high-dimensional data in chemical processes

$$L = \left\{ (\boldsymbol{F}_l, \boldsymbol{T}_l) \middle| \mathrm{l} = 1, 2, \ldots, \mathrm{L}; \boldsymbol{F}_l \in \boldsymbol{R}^l; \boldsymbol{T}_l \in \boldsymbol{R}^l \right\} \tag{12}$$

where there are J attributes of input $\boldsymbol{F}_l$ and O attributes of output $\boldsymbol{T}$ in each training sample. Based on the training sample set L, the flowchart of the IDA-ELM neural network model is proposed as the following.

(2) Using the IDA to filter and compress data. First, We set the high-dimensional input vector comes from the complex chemical processes in set L as the variable in the IDA algorithm. Then, according to the product processes we choose the suitable U and Q. Finally, Calculate the changes in activity$\Delta U_{act}^{0,l}$, structure $\Delta U_{str}^{0,l}$ and intensity $\Delta U_{int}^{0,l}$ using Eqs. (8)-(10), to represent that with a collection:

$$P = \{\Delta \mathrm{U}_{\mathrm{act}}^{0,\mathrm{l}}, \Delta \mathrm{U}_{\mathrm{str}}^{0,\mathrm{l}}, \Delta \mathrm{U}_{\mathrm{int}}^{0,\mathrm{l}} | \mathrm{l} = 1, 2, \ldots, \mathrm{L}; \Delta \mathrm{U}_{\mathrm{act}}^{0,\mathrm{l}} \in \boldsymbol{R}^{\mathrm{l}}; \Delta U_{str}^{0,l} \in \boldsymbol{R}^l; \Delta U_{int}^{0,l} \in \boldsymbol{R}^l \Big\} \tag{13}$$

(3) The establishment of ELM neural network. Set P as the input vector of ELM and the vector $\{\boldsymbol{T}_\mathrm{l} | \mathrm{l} = 1, 2, \ldots, \mathrm{L};\ \boldsymbol{T}_\mathrm{l} \in \boldsymbol{R}^\mathrm{l}\}$ in training set L as the expected output. So the number of neurons in input layer is$Count_{in} = 3$, and that in output layer is$Count_{out} = O$.

(4) Training process. After the processing of high-dimensional data in complex chemical processes we can get the outcome P. Set P in accordance with the ELM learning algorithm for training and record the connection weights $\boldsymbol{\alpha}$ between the hidden layer and the input layer of the ELM neural network, the connection weights γ between the hidden layer and the output layer and the threshold $\boldsymbol{t}$ of hidden layer.

(5) Generalization process. First, We use a set of samples that is different from we used in training process to act as the generalization sample set$L' = \{(\boldsymbol{F}_l', \boldsymbol{T}_l') \big| l = 1, 2, \ldots, L; \boldsymbol{F}_l' \in \boldsymbol{R}^l; \boldsymbol{T}_l' \in \boldsymbol{R}^l\}$. Second, we use the method like (2) and the data set L' to calculate the activity$\Delta U_{act}^{0,l}$, structure $\Delta U_{str}^{0,l}$ and intensity $\Delta U_{int}^{0,l}$ of the generalization sample sets. Third, use the ELM trained in (4) to calculate the result of generalization$\{\boldsymbol{W_l} \big| \mathrm{l} = 1, 2, \ldots, \mathrm{L}; \boldsymbol{W_l} \in \boldsymbol{R}^l\}$. Finally, comparing that with expected output set $\{\boldsymbol{T}_\mathrm{l}' | \mathrm{l} = 1, 2, \ldots, \mathrm{L}; \boldsymbol{T}_\mathrm{l}' \in \boldsymbol{R}^\mathrm{l}\}$ and calculate the generalized relative error Q by Eq. (11).

$$\mathrm{Q} = \frac{|W - T'|/T'}{l} \tag{14}$$

The composition chart is shown in Fig. 1.

3.3.2. The framework of energy analysis and optimizes

As can be seen in the composition chart in Fig. 1, the framework can be elaborated as follow:

(1) Selecting the data of chemical plants. In the first step, we select the last few periods. This data should contain the related information with the production of the produce processes. Then, in step two we get the training sample sets and generalization sample sets. Generalization sample sets are the data of the time period to be analyzed. The training sample sets are from the same plants but in different time periods, and those sets must have the same attributes with the generalization sample sets.

(2) Calculating the optimization index. After the calculating of IDA method (step three), we have rejected the abnormal and noise data, and reduced the chemical processes data dimension. The calculate results of IDA is the optimization indices of our framework. We set the activity, structure and intensity of each chemical processes as the optimization indices. The optimization indices can be used to analyze energy optimization of each process.

(3) The optimization indices are the input data of ELM, and the output index of chemical processes is the output of ELM. After the training time, the ELM can simulate the process of the current plants. So in the generation time, we can get the expected outputs of the input data.

(4) After the process of ELM (step 4) we can get the optimization indices and the productions that calculated by our framework. How to control the actual production to reach the production of our framework is the optimization problem we need to deal with. In order to analyze this problem, in step five we select a period of time, and use relationship of the production and the optimization indices to optimize and analyze the energy of chemical processes plants (in step six and seven).

4. Case study: energy optimization and analysis of the complex chemical process based on the IDA-ELM

4.1. Energy optimization and analysis of Ethylene production systems

4.1.1. Data analysis

In the ethylene industry, different companies will take a different approach to divide energy utilization boundary and calculation method. We divide the ethylene production plants with DB 37/751-2007 and GB/T 2589-2008l [44]. As a key factor in the process of complex chemical industries, the ethylene production process consists of two aspects: cracking and separation. And separation part can be divided into three aspects: a rapid cooling, a compression and a separation part. Fig. 2 shows the schematic flow diagram of an ethylene plant.

Raw materials, fuel, power consumption, and the product are directly related to the production efficiency in ethylene production system. The crude oil, steam, electricity, water and fuel are the input indexes of boundary region according to the ethylene production process. In literature [45] we can see the units of the inputs are all converted to GJ. Therefore, in this paper, we set the ethylene production as the output of the IDA-ELM network, which refers to the seven kinds of crude total and amount of oil, fuel, steam, water, electricity as the input of the network. The required crudes, the production of ethylene and energy types (water, steams, fuels, electricity) of six ethylene plants in 2011 are shown in Fig. 3 and Fig. 4, respectively.

4.1.2. Energy optimization and analysis of Ethylene plants

The objective of our experiment is to analyze the recorded data from six main ethylene production plats out of China's seven types of technology in producing ethylene from 2009 to 2012. The training data is derived from each plat of 2009–2011 while the generalization data comes from the data in 2012. In our experiment, we compared the effectiveness and stability between the IDA-ELM network and the original ELM network in ethylene plant.

From the result in Fig. 5, we can get the minimum generalization error when the number of nodes of the hidden layer is 13. So we compare the best performance of ELM which has 13 nodes in the hidden layer and the best performance of IDA-ELM which has 4 nodes in the hidden layer. And we also present the result that ELM only has 4 nodes. The experimental results are shown in Table 1.

From the result in Table 1, in ethylene production plants, when

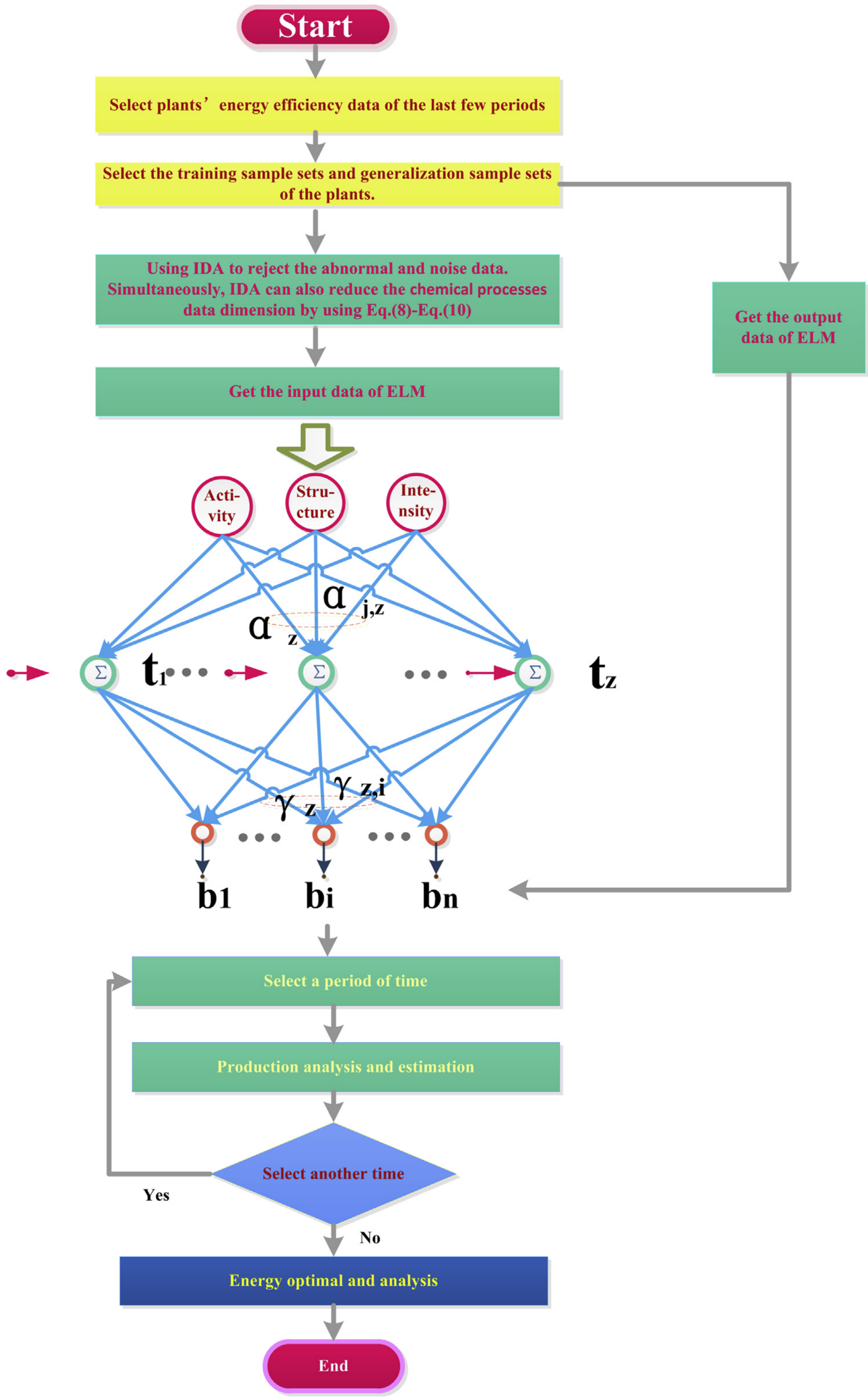

Fig. 1. IDA-ELM composition chart.

the hidden layer node is 4, the relative error of ELM is larger than that of IDA-ELM, and if we want to achieve the same relative error with IDA-ELM, we need to increase the number of hidden layer nodes to 13. At the same time, the training time of ELM was significantly increased compared with that of the improved IDA-ELM. Based on the above conclusions, it can be seen that the generalization results of IDA-ELM is more similar to the original ethylene production than that of ELM.

Therefore, the error of a certain amount of ethylene production analysis can be decrease using the IDA-ELM model for production

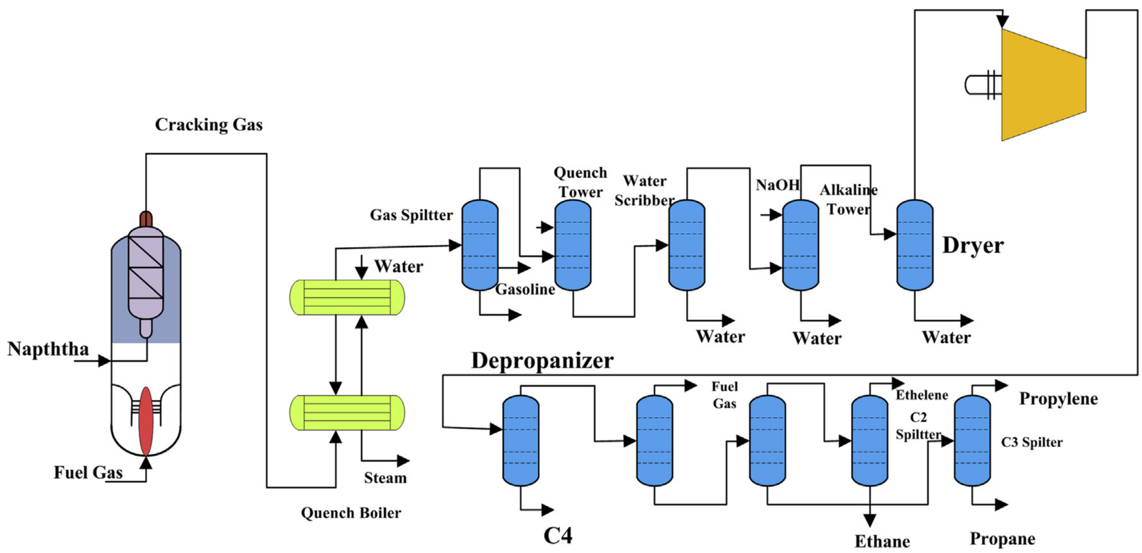

Fig. 2. Schematic flow diagram of an ethylene plant.

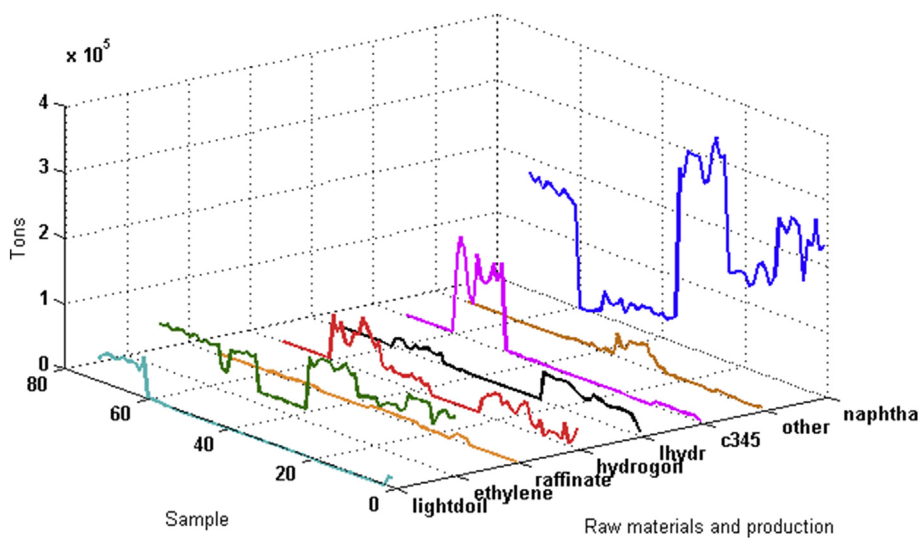

Fig. 3. Row materials and output of ethylene plant in 2011.

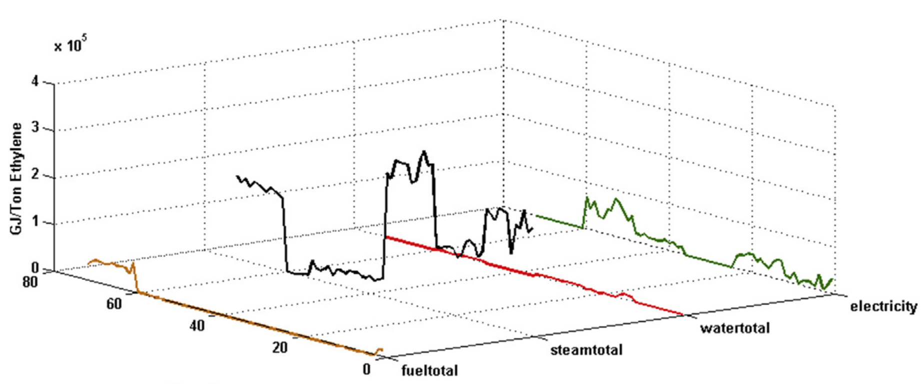

Fig. 4. Energy consumption of ethylene plants in 2011.

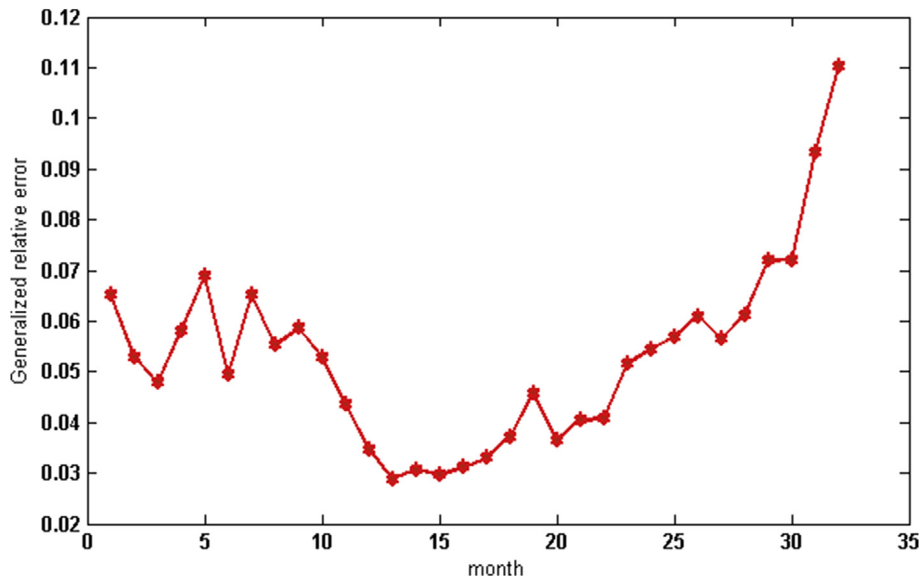

Fig. 5. The relationship between the number of nodes of the hidden layer and the generalization error of ELM.

Table 1
Modeling error of ethylene system.

Ethylene system	IDA-ELM	ELM	ELM
Hidden layer node	4	4	13
Training relative error/%	3.1393	4.8048	1.4202
Training time (ms)	6.0135	7.6892	8.5072
Generalized relative error/%	3.1908	6.7317	3.072

Table 2
Index decomposition data of Ethylene plant in 2013.

Month	Activity	Structure	Intensity	Product
1	−2.0097	−0.46596	5.20975	390301.44
2	−3.8142	0.62159 8	4.27424	371865.02
3	−8.6744	−3.12546	12.1044	374657
4	−45.625	−18.2626	49.4956	323861
5	−12.205	−9.7112	14.6558	382364.56
6	2.76885	1.094839	−4.3388	393276
7	5.73404	0.991632	−8.6340	401631
8	5.86687	−2.55024	−10.476	411988
9	−4.1813	−2.05441	4.21133	383266
10	4.96928	−2.47657	−3.6992	408829
11	9.55827	−0.61441	−13.838	416953
12	7.68208	1.002252	−9.0320	406887

analysis. We analyzed the sum of six ethylene production plants in each month of 2013, Table 2 shows the results of data that processed by IDA. Fig. 4 shows the actual production of ethylene and the production estimated by IDA-ELM.

From Fig. 6 we can see that the ethylene production of the fourth month is the least one. Based on the IDA analysis indicators of Table 2 we know, in April, the impact of ethylene production is the smallest, the structure of the plant is the least, and the intensity of production is the biggest. In November, production of ethylene is the highest, the production activities value is maximum and the strength influence value is minimum. Thus, activities play the most important role in the effect of ethylene production, and the bigger the activities value is, the smaller the intensity value is and the higher the ethylene production is, and vice versa.

In the year of 2013, the trend of the change of ethylene production is the same as that calculated by the model. However, there still some difference between the result of the model and actual production, In addition to January and September. For example, in the fifth month which is the largest different month, the impact value of the production activity is: −12.21, the plant structure influence value is: −9.71, the influence value of the production intensity is: 14.66, the total output is 382364.6 Tons, but the model estimated output is 397257 Tons. According to the energy efficiency analysis model, the factory can improve the impact value of production activity, and reduce the influence of the intensity of production. In order to increase the production activity we should improve the production of current plant. For example, Fig. 7 shows the optimal results of ethylene plants in the 1st, the 5th and the 9th month. In the 1st month, when the production of plant 1 has been increased to 0.55%, the activity will be increased to 6.88% and the intensity will be decreased to 5.94%. At the same time, if we want to decrease the intensity of production, the energy consumption of current plant must be decreased. So decrease the consumption of crude, oil, fuel, steam, water or electricity can decrease the consumption of energy. The ethylene industry factory can adjust the input of the following months to reach the best output value, in order to stabilize production, improve energy efficiency.

Fig. 8 shows the optimal percentage of the ethylene plants. From Fig. 8 we can see, after the processing of IDA-ELM, we can increase the production of ethylene by 5.33%.

4.2. *Energy optimization and analysis of PTA solvent systems*

4.2.1. *Data analysis*

The consumption of acetic acid is an important indicator to measure the advancement and effectiveness of PTA technology. And the most important way to reduce the consumption of acetic acid is the optimal control of the solvent system. Solvent system can be divided into three parts: the solvent dehydration tower, the re-boiler and the reflux tank. We focus on the analysis of the solvent dehydration tower. Fig. 9 shows the schematic flow diagram of a solvent dehydration tower.

The main factors influencing the acetic acid content in the top of the PTA solvent system were: the water reflux, the feed composition (acetic acid content), the feed quantity, the NBA main reflux, the NBA side reflux, the temperature point between the 44th tray

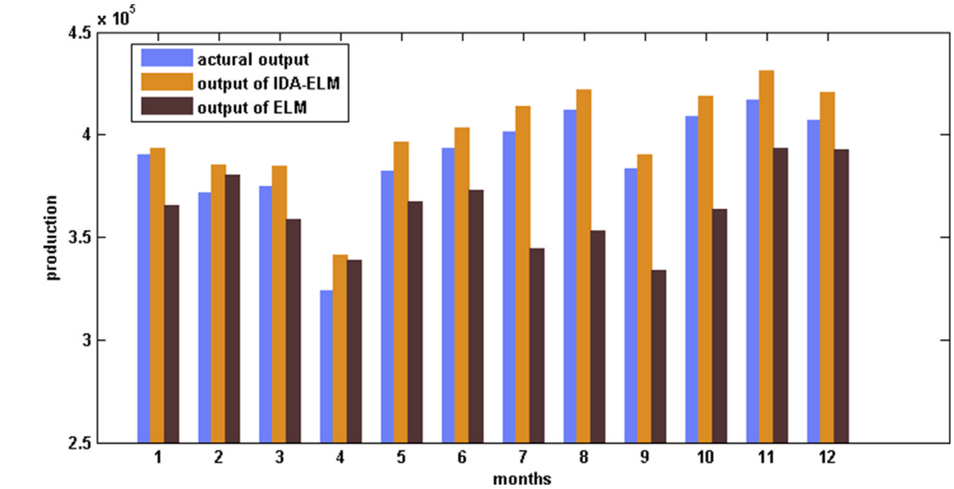

Fig. 6. Comparison of ethylene product in 2013.

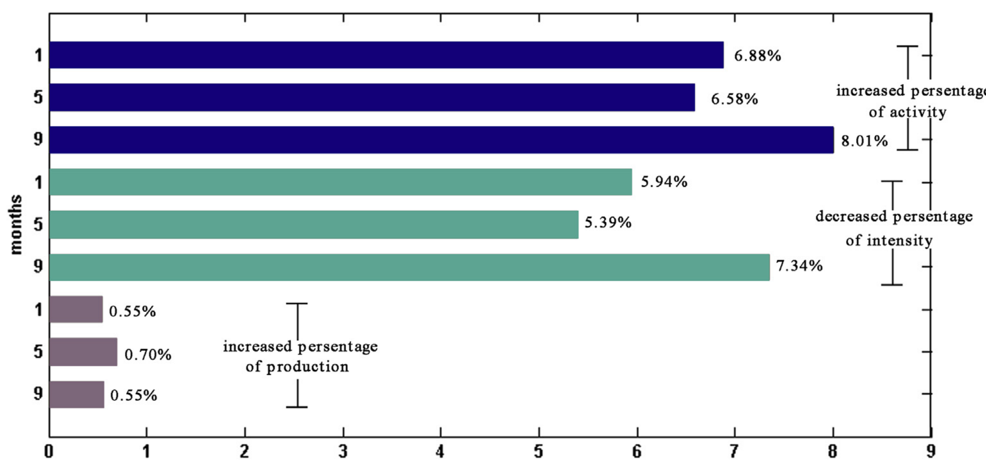

Fig. 7. Optimal results in ethylene plants.

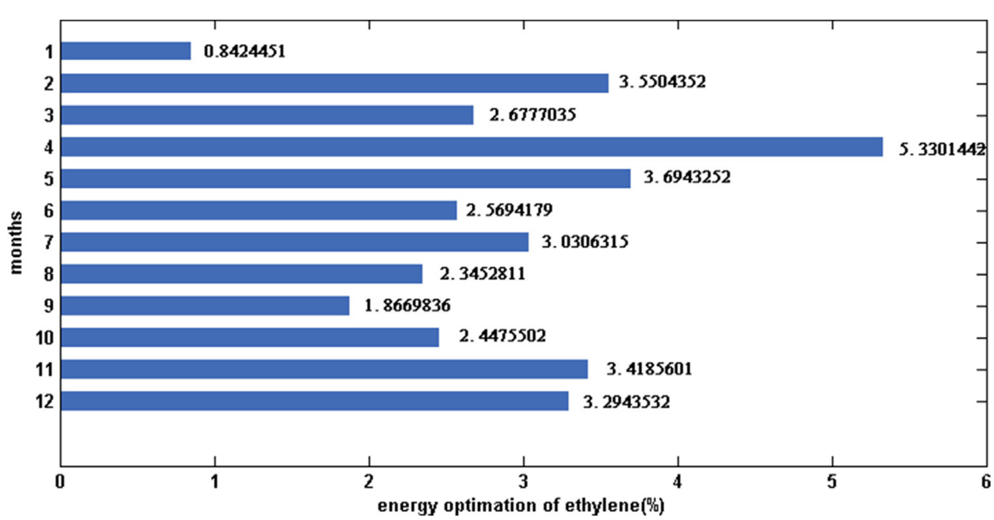

Fig. 8. Optimal percentages of the ethylene plants.

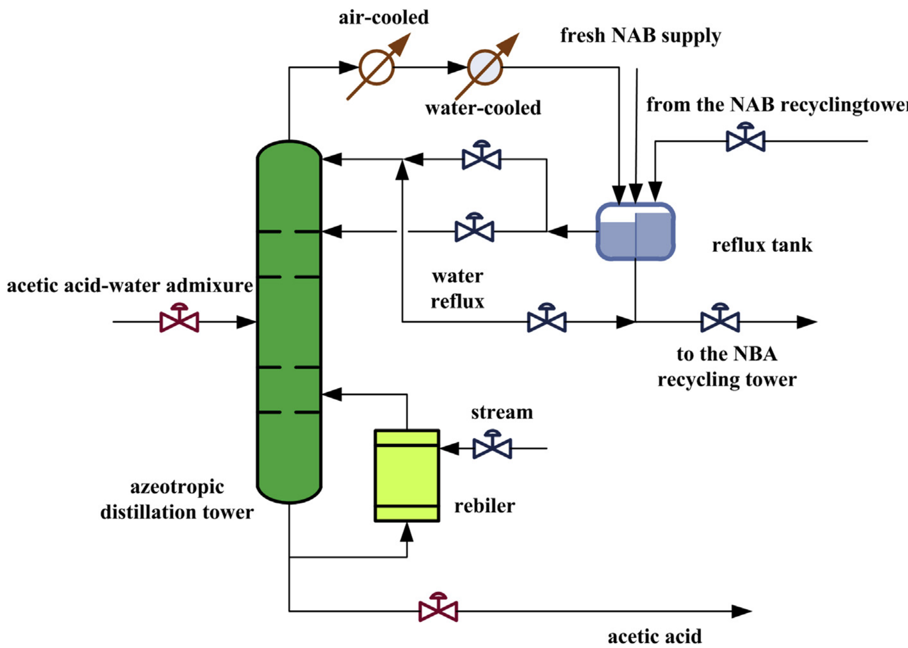

Fig. 9. Schematic flow diagram of a solvent dehydration tower.

and the 50th tray, the tray temperature near the sensitive plate, the steam flow, the reflux temperature, the temperature of the top tower, the temperature point above the 35th tray, the temperature point between the 35th tray and the 40th tray, the tray temperature near the sensitive plate, the produced quantity of the top tower, the feed temperature, the controllable temperature point between the 53rd tray and the 58th tray and the reflux tank level. The output variable of the process model is the conductivity of the top tower, which can reflect the acetate acid content of the top tower.

The consumption reduction of the acetic acid is a significant goal in improving economic benefit. In order to verify the practical value of IDA-ELM network, we applied it in the production of PTA. We use IDA-ELM for modeling and analyzing the consumption of acetic acid to analyze the production of PTA solvent system. There are 17 main input variables in PTA solvent that impact the acetic acid consumption. But because of the determination of the content of acetic acid is difficult, so we use the electric conductivity of azeotrope tower overhead to indirectly reflect the changes of acetic acid content [46]. So the output of IDA-ELM is the electric conductivity of azeotrope tower overhead. The partial of the input variable is shown in Fig. 10.

4.2.2. Energy optimization and analysis of PTA solvent system

For the 17 factors mentioned above, the factors that affect the consumption of acetic acid are extracted by using the IDA method to extract the feature of high dimensional data. We picked the data from PTA solvent system during two months of 2011, among them, 144 of the data are used as training data, and 76 of the data are used as generalization data. The sum of influencing factors is treated as the total amount of energy consumption, and electrical conductivity (acetic acid) is treated as the activity level. We use Eq. (8), Eq. (9) and Eq. (10) to calculate the production activities, the plant structure and the intensity of production which are the three energy efficiency indicators. The indicators are used as input data of ELM, and electrical conductivity is the output data.

From the result in Fig. 11, we can get the minimum

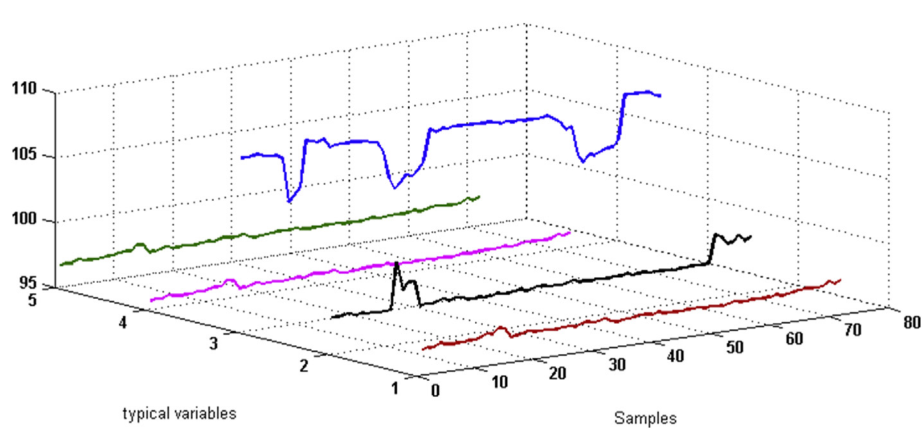

Fig. 10. The partial of the input variables of a PTA plant.

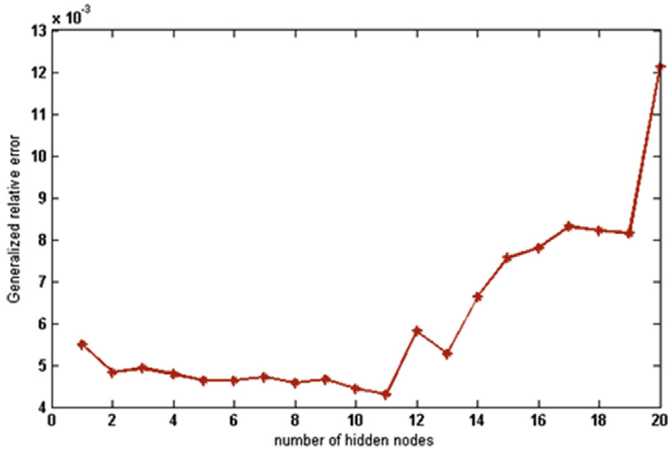

Fig. 11. The relationship between the number of nodes of the hidden layer and the generalization error of ELM.

Table 3
PAT System modeling error contrast.

PTA system	IDA-ELM	ELM	ELM
Hidden layer node	5	5	11
Training relative error/%	0.20398	0.44312	0.23795
Training time (s)	0.072228	0.078779	0.8226
Generalized relative error/%	0.22853	0.4328	0.41185

generalization error when the number of nodes of the hidden layer is 11. So we compare the best performance of ELM which has 11 nodes in the hidden layer and the best performance of IDA-ELM which has 5 nodes in the hidden layer. And we also present the result that ELM only has 5 nodes. Table 3 describes the error comparison results of IDA-ELM and ELM in the modeling of PTA production system.

From Table 3 we can see, in PTA system. When there are 5 nodes in hidden layer, the generalization relative error of IDA-ELM is less than that of ELM, and if we want to achieve the same training relative error, we need to increase the number of hidden layer nodes to 11. Even so, the training time of ELM which has 11 nodes in hidden layer is more than that of IDA-LEM which only has 5 nodes in hidden layer. In conclusion, the generalization of IDA-ELM is more similar to that of the original acetic acid conductivity than that of the traditional ELM.

So it is clear that IDA-ELM can be more accurate to analyze the electric conductivity of acetic acid in energy efficiency analysis. We analyze the acetic acid conductivity of PTA equipment in a month of 2012, Table 4 are the data processed by IDA. This month's acetic acid actual conductivity and the conductivity of the IDA-ELM model calculated as shown in Fig. 9.

Table 4
PTA plant index decomposition data.

Groups	Activity	Structure	Intensity	Conductivity of acetic acid
1	6.445491	−0.38474	−23.5885	291.8624
2	−63.2495	−0.05044	57.26559	288.3777
3	−29.9225	−0.20663	19.46031	290.0379
4	59.38211	−0.06801	−37.6364	294.5008
5	31.017	−0.33981	22.25351	293.0844
6	−35.2237	−0.11346	30.83752	289.7705
7	−32.4309	−0.11867	18.14145	289.9082
8	9.338387	−0.76818	−24.1398	292.0265
9	10.44481	−0.57294	−6.762	292.0713
10	−27.2516	−0.14201	43.51603	290.1707
11	6.912025	−0.7507	−23.643	291.9041
12	58.87342	−0.98962	−70.0397	294.5301

From Fig. 12 we can see that the acetic acid conductivity in the second group of data time is minimal, based on the IDA analysis index Table 4, it is clear that in the second groups of data time PTA production activities have a minimum impact on the production intensity, and the intensity of production is at the peak. The 12th group of data time reaches the highest acetic acid conductivity, and the production activities have a largest impact on the production intensity, the intensity of production is the minimum value. Thus, the larger the activities impaction is and the less the production intensity is, the higher the acetic acid conductivity is and vice versa.

In this period of time, the trend of the change of the actual production of PTA is the same as that of the model. However, there are still some different in each group. For example, in the seventh and ninth groups of data, the actual conductivity of acetic acid is larger than the estimation of IDA-ELM model. In the seventh group: The influence of production activity is −32.43, the structure of the plant is −0.11867, the intensity of production is 18.14, the conductivity of acetic acid is 289.91, but the model is estimated to 289.82. According to the energy efficiency analysis model, the factory can reduce the impact value of activity, and improve the influence of the intensity, in order to decrease the activity we should reduce the energy consumption of current plant. Meanwhile, if we want to increase the intensity, we should decrease the conductivity of current plants. For example, Fig. 13 shows the optimal results of PTA plants in the 2nd, the 4th and the 7th group. In the 2nd month, when the conductivity of plant 1 has been decreased to 0.017%, the activity will be decreased to 1.957% and the intensity will be increased to 1.850%. The PTA industry factor can adjust the input of the following times to reach the best output value, in order to stabilize production, improve energy efficiency.

Fig. 14 shows the optimal percentage of the PTA plants. From Fig. 8 we can see, after the processing of IDA-ELM, we can decrease the conductivity of PTA plants by 0.046%.

5. Conclusion

In this paper, we propose an IDA-ELM energy optimization and analysis modeling method to deal with the data of complex chemical processes. The IDA-ELM can not only reduce the dimensionality of the high-dimensional data, but also filter redundant information and reduce the impact of noise effectively. What's more, the calculated result of the IDA has been treated as the optimization indices to deal with the optimization problem. And the result of the ELM is the output reference of the current process. Through the relationship between the optimization indices and the output we explained in part 4, we can optimize and analyze the complex chemical processes. Compared with the previous work, the advantages of proposed method are converges faster, and will not trap into local minimization. What's more, our proposed method is applied to the main production plants of the ethylene production system and the PTA solution system in complex chemical processes. In our experiment, the production of ethylene plants can be increased by 5.33%, and the conductivity of PTA plants can be reduced by 0.046%. Compared with the ELM, the proposed method has the advantages of less hidden layer nodes, smaller training error and faster training speed. Meanwhile, we analyzed the conductivity of ethylene plants in 2013 and the conductivity of the PTA acetic acid in a month of 2012. The experimental results show that the IDA-ELM can optimize the improvement direction of production capacity and improve the energy efficiency of plants more accurately. Therefore, the IDA-ELM has the capacity of achieving the goal of improving the efficiency of the complex

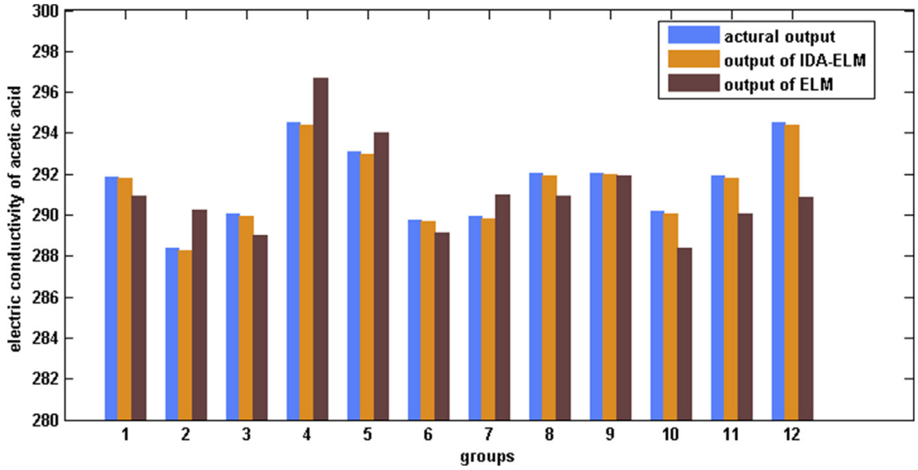

Fig. 12. Analysis on the acetic acid conductivity of IDA-ELM and ELM.

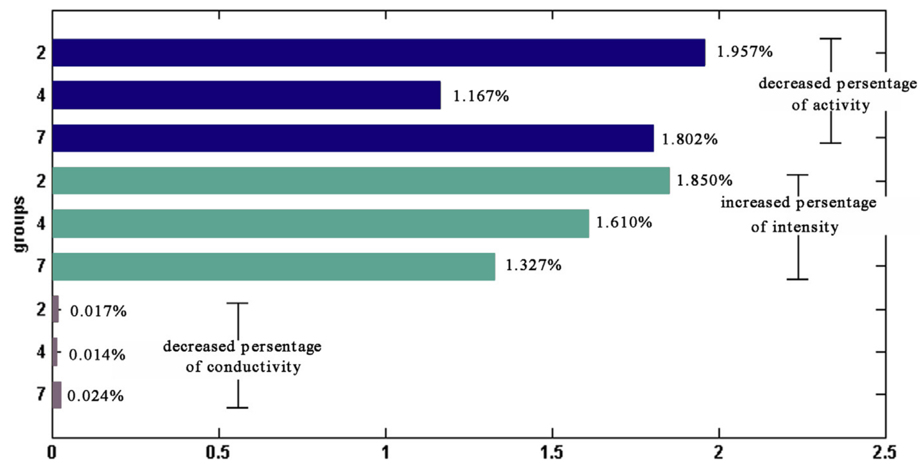

Fig. 13. Optimal results in PTA plants.

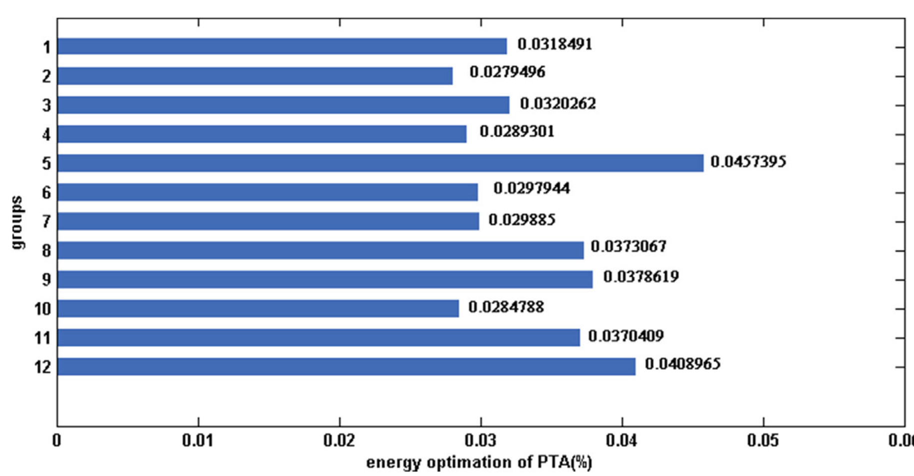

Fig. 14. Optimal percentages of the PTA plants.

chemical process.

In our future studies, we will take the effect of economic development, capital and environmental planning on the energy optimization of the complex chemical industry into account. Moreover, we will investigate and integrate other methods, such as the augmenting topologies neural network to enhance the generality of our method. Furthermore, we will collect the data of per second or per minute to achieve the real time application and focus on more detailed time density and real-time production data in order to improve the real time energy optimization of the complex chemical industry.

Acknowledgments

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