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Energy modeling and saving potential analysis using a novel extreme learning fuzzy logic network: A case study of ethylene industry

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HIGHLIGHTS

- An effective extreme learning based fuzzy logic network is proposed.
- ANN integrated with FIS technology is adopted for energy modeling and analysis.
- Slack variables are predicted using ELM for energy saving potential analysis.
- An energy modeling and saving potential analysis framework is established.
- A quantitative energy saving potential of crude oil with 8.82% is achieved.

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ABSTRACT

Comprehensive energy modeling and saving potential analysis play a key role in sustainable development of complex petrochemical industry. However, it is difficult to make effective energy modeling and saving potential analysis due to the characteristics of uncertainty, high nonlinearity, and with noise of the data collected from the practical production. To deal with this problem, an energy modeling and saving potential analysis method using a novel extreme learning fuzzy logic network is proposed. In the proposed method, Mamdani type fuzzy inference system and multi-layer feedforward artificial neural network are integrated. First, the original ethylene production data is fused into a comprehensive energy consumption index. Then the index is fuzzified as outputs instead of precise values. Finally, an extreme learning algorithm based on Moore-Penrose Inverse is utilized to train the network efficiently. Three levels of energy efficiency of "low efficiency, median efficiency and high efficiency" can be effectively classified using the proposed method. For "low efficiency", valid slack variables are predicted for finding the direction of improving energy efficiency and then analyzing the energy saving potential. The performance and the practicality of the proposed method are confirmed through an application of China ethylene industry. Simulation results show that low-efficiency samples can be effectively improved to be high-efficiency samples and the energy saving potential in terms of the crude oil reduction amount is indicted as 8.82%.

1. Introduction

Petrochemical industry is a very important industry for any developed and developing country. The development level of petrochemical industry is usually regarded as a symbol to evaluate the industrialization level for a country. However, petrochemical industry is energy-consuming, where many resources are consumed. China is an industrial powerhouse involving many petrochemical factories. As the most crucial part of petrochemical industry, ethylene industry consumes a large amount of crude oil, fuels, electricity, steam, and water for production. China Petrochemical Corporation and China National Petroleum Corporation represent the development level of China ethylene industry. Compared with some advanced countries, the energy efficiency of China ethylene industry is much lower [1,2]. What is more, over 50% of operating cost in ethylene industry is occupied by energy consumption of ethylene plants [3]. This current situation provides a considerable space for energy efficiency improvement and energy saving. Therefore, energy modeling between the energy consumption of crude oil, fuels, electricity, steam, and water and the energy efficiency becomes of great importance for efficiency improvement and energy saving potential analysis of petrochemical industry so that some limited available resources like oil and fuel can be better used, which can bring

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not only direct economic benefit, but also considerable environmental benefit. Unfortunately, energy consumption data collected from production process are usually uncertain and noisy, which causes a bad influence on energy efficiency analysis and energy saving potential analysis.

In the aspect of energy efficiency analysis, index decomposition analysis (IDA) and stochastic frontier analysis (SFA) are two widely used methods. In the IDA method, energy consumption changes are decomposed into three effects covering the properties of activity, structure and intensity [4,5]. The SFA is a technology based on statistical regression methods, where a distribution form for inefficiency terms is required to specify and a function type for production frontiers should be determined [6]. Although the IDA and SFA methods have been widely used in various departments, improvement factors for energy efficiency cannot be provided. Data envelopment analysis (DEA) is an alternative for providing improvement factors of energy efficiency. DEA is a non-parametric method. DEA can avoid any assumptions with the help of mathematical programming and provide slack variables for finding the direction of improving energy efficiency [7,8]. However, measurement errors and statistical noises are not taken into consideration in DEA. The uncertain and noisy characteristic of the monthly data collected from actual production may result in erroneous evaluation of DEA [9,10]. In addition, the DEA method relies on the historical inputs and outputs. As a result, DEA cannot evaluate planned investments for future production because there are no corresponding outputs to match the inputs. In summary, the energy consumption data with uncertainty and noise should be effectively dealt with and valid slack variables should be predicted for making accuracy energy consumption modeling and saving potential analysis.

For dealing with uncertain and noisy energy consumption data, fuzzy logic can be adopted. The notion of fuzzy set was innovatively put forward by Zadeh [11]. Mamdani type fuzzy inference system [12,13] has been proved to be a satisfactory and effective tool to handle data accompanied by uncertainty and noise. In the field of energy efficiency evaluation, Azadeh et al. [14] adopted the triangular fuzzy numbers instead of crisp data as the input and output for energy analysis of power generator sector. Han et al. [15] introduced fuzzy theory into energy efficiency analysis of petrochemical industries. For modeling, artificial neural network (ANN) is a powerful nonlinear modeling tool learning the relationship between inputs and target outputs. ANN has been widely used for modeling and predicting [16]. Ying et al. [17] combined fuzzy logic and error back propagating (BP) neural network for load modeling of power industry. Liu et al. [18] established ANN-based models for wind speed prediction. Neural network models based on BP algorithm has some drawbacks, like slow learning speed and easily falling into local minimum [19,20]. A competitive model named Extreme Learning Machine (ELM) was designed by Huang et al. [21,22] in 2004. Moore-Penrose inverse is used in ELM to achieve extremely fast training speed and avoid falling into local minimum. Recently, ELM has attracted more and more attention in fields of scientific researches and engineering applications [23–25]. Han et al. [26] proposed an improved ELM evaluation method focusing on the energy conservation and emission reduction of complex petrochemical systems. ELM-based methods are also used in soft-sensing model development and achieved satisfactory performance [27,28]. Hence, slack variables can be accurately predicted using ELM to make future efficiency evaluation.

In order to make accuracy energy modeling and saving potential analysis for complex petrochemical industry, a novel extreme learning fuzzy logic network (ELFLN) is proposed in this paper. In the proposed method, Mamdani type fuzzy inference system and multi-layer feedforward artificial neural network are integrated to deal with the energy data with the characteristics of uncertainty, high nonlinearity, and with noise. First, the fuzzy inference replaces the hidden layers of artificial neural network. Then the proposed framework takes fuzzy membership degrees of comprehensive energy consumption index as outputs. Finally, an extreme learning algorithm based on Moore-Penrose Inverse is utilized to train the proposed ELFLN efficiently. Three levels of energy efficiency of "low efficiency, median efficiency and high efficiency" can be effectively classified using the proposed ELFLN. For "low efficiency", valid slack variables are predicted using ELM for finding the direction of improving energy efficiency and then analyzing energy saving potential. To validate the performance and the practicality of the proposed methodology, an energy consumption index model was established using the proposed ELFLN model for China ethylene industry. Simulation results show that low-efficiency samples can be effectively improved to be high-efficiency samples and the energy saving potential can be calculated out.

The remaining part of this paper is arranged as follows: Section 2 contains some preliminaries of fuzzy neural network (FNN), ELM and DEA; the proposed ELFLN method is specifically introduced in Section 3; Section 4 provides the case study of energy modeling and saving potential analysis of ethylene industry based on the proposed ELFLN method; finally, Section 5 gives conclusions.

2. Preliminaries

2.1. Combination of ANN and FIS

In this study, Mamdani type FIS is selected to enhance ANN with the ability of processing uncertain and noisy data. ANN and FIS can be combined shown in Fig. 1.

Layer 1 is the input layer. Each node is connected with corresponding input variable x_i directly. The layer transmits input vector $\boldsymbol{x} = [x_1 \ \ x_2 \ \ \dots \ \ x_n]^T$ to the next layer and the node number is $N_1 = n$.

Layer 2 is the fuzzification layer. Each node represents an input linguistic variable (high, median, low, etc.). The membership degree

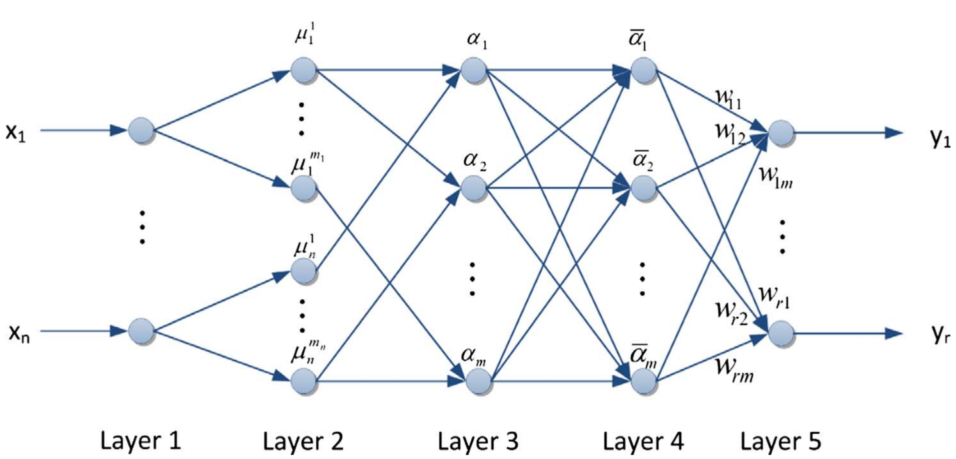

Fig. 1. FNN based on multi-layer feedforward neural network.