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Energy optimization and prediction of complex petrochemical industries using an improved artificial neural network approach integrating data envelopment analysis

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A B S T R A C T

Since the complex petrochemical data have characteristics of multi-dimension, uncertainty and noise, it is difficult to accurately optimize and predict the energy usage of complex petrochemical systems. Therefore, this paper proposes a data envelopment analysis (DEA) integrated artificial neural network (ANN) approach (DEA-ANN). The proposed approach utilizes the DEA model with slack variables for sensitivity analysis to determine the effective decision making units (DMUs) and indicate the optimized direction of the ineffective DMUs. Compared with the traditional ANN approach, the DEA-ANN prediction model is effectively verified by executing a linear comparison between all DMUs and the effective DMUs through the standard data source from the UCI (University of California at Irvine) repository. Finally, the proposed model is validated through an application in a complex ethylene production system of China petrochemical industry. The optimization result and the prediction value are obtained to reduce energy consumption of the ethylene production system, guide ethylene production and improve energy efficiency.

1. Introduction

Nowadays, energy conservation and emission reduction of the industry is required to meet the challenges of the sustainable development. And in complex petrochemical industries, energy optimization and prediction are effective means to achieve both environmental and economic goals. Wherein, the ethylene industry is one of the most key parts of the petrochemical industry. According to statistics data, China Petrochemical Corporation's ethylene production was 10,420 kt/a, and the average fuel and power consumption (converted to the standard oil) was 571.39 kg per ton of ethylene in 2014 [1]. The ethylene production capacity and the average fuel and power consumption of China National Petroleum Corporation was 4976 kt/a and 616.7 kg per ton of ethylene in 2014, respectively [2]. The energy efficiency of ethylene industries in China is significantly lower than that in the advanced countries, and there is great improvement space for energy efficiency in China ethylene industries. Moreover, the energy consumption cost of ethylene production plants took up over half of the operation cost [3]. Therefore, studying about energy optimization and prediction of ethylene industries is beneficial for the sustainable development of Chinese economy.

Currently, the mean method and the optimal index method are commonly used by enterprises to analyze the energy efficiency [4]. Because energy efficiency values contain indexes and influencing factors, and various indexes make different effects to energy efficiency factors, these methods cannot provide the energy efficiency benchmark of indexes or excellent factors to optimize the practical state of the energy usage. Han et al. proposed the energy efficiency evaluation method of ethylene production plants based on Analytic Hierarchy Process (AHP) and Data Envelopment Analysis (DEA), with better results [5]. Meanwhile, Han et al. multi-level analyzed the month and year energy efficiency of the petrochemical process under different technologies and scales [6]. However, all these methods did not take the impact factor of crude oils into consideration. In addition, Dias et al. used chemical and biological alternated step-size control to analyze the Dengue vector control problem in a multiobjective optimization approach [7]. Grom et al. used a generalized kinetic model and an appropriate algorithm to evaluate the rate parameters and subsequent regression of the chemical engineering [8]. However, the economic cost of

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Nomenclature

DEA	data envelopment analysis
ANN	artificial neural network
DMU	decision making units
UCI	University of California at Irvine
BP	back propagation
C4	Carbon 4
C^2WH	Charnes, Cooper, Wei, Huang
x_{ij}	ith input of DMU_{-j}
y_{rj}	rth output of DMU_{-j}
α	weight coefficients of m inputs
β	weight coefficients of s outputs
ω_j	the weight vector of inputs and outputs
ε	non-Archimedean infinitesimal
τ_t^- and τ_t^+	the slack variables
λ	the optimum values of the DMU_{-j0}
$X = (x_1, x_2, \ldots, x_i, \ldots, x_m)^T$	the input vector
$V = (v_1, v_2, \ldots, v_j, \ldots, v_l)^T$	the weight vector of the input-layer to the hidden-layer
$W = (w_1, w_2, \ldots, w_k, \ldots, w_n)^T$	the weight vector of the hidden-layer to the output-layer
$g(x)$	The sigmoid function
$Y = (y_1, y_2, \ldots, y_j, \ldots, y_l)^T$	the output vector of the hidden-layer
$O = (o_1, o_2, \ldots, o_k, \ldots, o_n)^T$	the output vector of the output-layer
$d = (d_1, d_2, \ldots, d_k, \ldots, d_n)^T$	the desired output vector

transforming petrochemical plants was not included. Therefore, this paper proposes the energy optimization and prediction method of China petrochemical industries based on the DEA-integrated artificial neural network (ANN) (DEA-ANN).

The DEA method is firstly proposed by the famous operational researchers Charnes, Cooper and Rhodes (CCR) in 1978 [9]. When it was applied in production apartment of multi-inputs and multi-outputs, the DEA was proved both sizeable effective and technological effective. As a result, the DEA method is satisfactory and effective with application in practical engineering fields [10], especially in the petrochemical industry. Sueyashi et al. studied the DEA method and the DEA window analysis to analyze the operational and environmental performance of the coal-fired power plant, respectively [11,12]. Han et al. evaluated the energy efficiency of ethylene industries based on the combination of interpretative structural model (ISM) and the traditional DEA [13]. Sueyoshi et al. studied the DEA radial measurement approach to optimize energy utilizations and environmental protections of Japanese chemical and pharmaceutical firms [14]. Bi et al. investigated the relationship between the fossil fuel consumption and the environmental regulation of China's thermal power generation by the DEA model [15]. Zhu et al. analyzed many factors influencing the energy use of an ethylene plant and evaluated the efficiency of the ethylene plants by principal component analysis (PCA) integrated DEA models [16]. Han et al. utilized the fuzzy DEA cross-model to analyze and evaluate the energy efficiency of Chinese ethylene production systems [17]. However, the results were easily affected by the quantities of samples and the numbers of input and output factors [18,19], and the energy saving is not predicted. When the quantities of samples are too small or the numbers of input and output factors are too large, more than one-third of efficiency values, which are obtained by the DEA model, are then set to 1 [20,21]. Moreover, the weight distribution of the input and output factors is generally unreasonable, so the maximum efficiency DMU of the DEA model was not obtained [22]. Therefore, the ANN is applied to analyze and predict the energy usage of the petrochemical industry.

The ANN algorithm is a learning algorithm used for the multi-layer feed-forward neural network (FNN). And the ANN with error back propagation (BP neural network) was designed by the research group led by Rumelhart and McCelland in 1986, based on the error back propagation algorithm [23]. The ANN is widely applied in prediction and optimization of different fields. Avramovic et al. used the ANN integrated genetic algorithm (GA) method to optimize the sunflower oil ethanolysis catalyzed by calcium oxide [24]. Jiang et al. studied an intelligent optimization models based on hard-ridge penalty and RBF for forecasting global solar radiation [25]. Meo et al. studied a new hybrid approach obtained combining a multi-objective particle swarm optimization (PSO) and ANN for the design optimization of a direct-drive permanent magnet flux switching generators for low power wind applications. [26]. Although the BP algorithm is a powerful supervised learning algorithm for training multi-layer FNNs [27,28], this gradient descent-based algorithm often suffers from problems of the local minima and slow convergence rate. Aiming at ameliorating the convergence properties of the BP neural network [29], many proposals have been made by researchers in the last twenty years. Dai et al. studied a two-phased and ensemble-scheme integrated BP (TP-ES-BP) algorithm, which could dispose the local minima of the standard BP (SBP) algorithm better, and overcome the limitations of individual component BP algorithm in classification performance [30]. In order to improve the learning convergence of the BP, some researchers have tried to integrate the BP with the PSO method or with the GA to overcome its shortcomings [31,32].

In order to overcome the insufficient of the DEA and the BP neural network and predict the energy usage better, Wu get the Travel & Tourism competitiveness rankings reasonably using the integrated method with the grey system theory (GST), the DEA, the ANN and the Borda count [33]. Olanrewaju et al. proposed an integrated approach, including logarithmic mean divisia index (LMDI), a type of index decomposition analysis (IDA), the ANN, and the DEA methods, to evaluate and optimize the energy efficiency of the industrial sector in Canada [34,35]. This paper proposed an integrated method based on the BP with the momentum factor and the DEA model to optimize and predict the energy usage of ethylene production plants in the petrochemical industry. First, in terms of the model accuracy and training time, the robustness and effectiveness of the DEA-BP model is better than the BP. And then the proposed approach utilizes the DEA model with slack variables to find the effective DMUs and obtain the optimized direction of the ineffective DMUs. Based on the energy efficiency analysis and optimization results of the DEA, we utilize the energy consumption data of crude oils, fuel, steams, water, electricity, and the productions of ethylene, propylene and carbon 4 (C4), as inputs and outputs of the BP, respectively. In the BP model based on the effective DMUs, we introduce the momentum factor to avoid the problems of the local minima and slow convergence. The proposed method is validated by applying in energy optimization of the production data, and prediction of the ethylene production system in China petrochemical industry. Meanwhile, the prediction values are obtained to reduce energy consumption of the ethylene production system, guide ethylene production and improve energy efficiency.

2. Experimental

The DEA method is a classic performance or efficiency evaluation method. The discrimination of analysis results are lowered by a large number of input and output factors. When input and