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Application of Artificial Neural Network in Rectification

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Authors' contributions

This work was carried out in collaboration between both authors. Both authors read and approved the final manuscript.

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Review Article

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ABSTRACT

Distillation is a unit operation process that uses the different volatility of various components in the mixture to separate or purify. The key problem has always been how to improve the separation effect of rectification. However, there are complex coordination, constraints and conflicts between the objective function and the input parameters of the rectification system, and it is difficult to obtain the optimal operating conditions by applying traditional control methods. With its powerful computing power and adaptive learning ability, the artificial neural network can establish the nonlinear correspondence between the objective function and multiple independent variables without relying on the mathematical model, which provides a powerful tool for the optimal operation and design of the distillation column. This article will introduce the basic principles, typical network models and development history of artificial neural networks, and summarize the application and research progress of artificial neural networks in distillation.

Keywords: Distillation; artificial neural networks; optimal operation; BP neural network.

1. INTRODUCTION

With the aggravation of the worldwide energy crisis and the rising oil price, people urgently hope to improve the production efficiency of unit operation devices and reduce energy consumption [1]. As one of the most common and important separation equipment in petrochemical production, distillation column has naturally become the object of most concern. Distillation control, as the most effective means to achieve the above objectives, has also been

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highly valued. In fact, the research of distillation control has experienced a long development period, and has formed a unique branch of chemical process control. However, its development is still unsatisfactory. Until the early 1960s, the control of distillation column still remained at the level of single loop control of several parameters. Although Shinskey et al. [2] put forward the idea of material balance and energy balance for the control of distillation column very early, further clarified the significance and purpose of distillation control, and further clarified the classification of distillation control, all this did not bring essential progress to distillation control. With the development of modern industry, people's research focus has shifted to the application of the results of theoretical research to the actual industrial production units, so as to realize a higher level of control of the industrial distillation column and further improve the economic benefits on the premise of ensuring the quality. However, because the distillation process has the characteristics of large lag, high model order, slow dynamic response, serious nonlinearity, many control variables, strong correlation of control loop and difficult on-line measurement, it is difficult to obtain the optimal operating conditions by using the traditional experimental method. Artificial neural network has the ability of nonlinear mapping, self-learning and strong fault tolerance. It has been successfully applied to the optimization of various processes in the process of distillation control. Artificial neural network ANN is a mathematical abstract model that imitates the behavior characteristics of human brain neural network. It processes information by adjusting the interconnected relationship between a large number of internal nodes [3]. The network is used to extract the features of the input target and obtain the corresponding output value. ANN has the functions of distributed storage and parallel processing of information, and has great advantages in solving the problems of incorrect nonlinear measurement data and large amount of information [4]. This paper systematically introduces the basic principle, typical network model and development history of artificial neural network, and summarizes the application of artificial neural network in distillation.

2. ARTIFICIAL NEURAL NETWORK AND ITS RESEARCH PROGRESS

Artificial neural network (ANN), also known as neural network or quasi neural network, is a simulated logic algorithm realized by simulating the processing mode of information in human brain. Each connection is similar to the synapse between neurons, which is used for the transmission of information between neurons; Neurons are interconnected with neurons to form a neural network, so as to obtain the final feedback [5]. In March 2016, AlphaGo and Li, the world champion of go and professional Nine Segment player, fought a man-machine war of go and won with 4-1 overall score. The news immediately caused an uproar. AlphaGo has adopted many new technologies, one of the most important of which is artificial neural network. As an important branch of artificial intelligence, neural network can simulate human brain to deal with some problems requiring high-intensity learning and calculation, so as to better realize artificial intelligence [6].

In 1943, famous scholars McCulloch and Pitts [7] proposed an M-P model, which is a mathematical study simulating nerve cells in human biology. The emergence of this model marks the birth of artificial neural network. By 1969, Minsky et al. [8] poublished the book perceptron, pointing out that the perceptron could not deal with the problem of high-order predicates and the difficulty of electronic circuit crossing. The neural network could not calculate a large number of neurons. The development of artificial neural network entered a low ebb, and the development of artificial neural network gradually stopped. Until the 1980s, new theories such as art network, cognitive machine network, Boltzmann machine theory and parallel distributed processing were constantly put forward, which solved the two problems put forward by Minsky, and the artificial neural network entered a new era of development [9-11]. In 1986, Hinton et al. [12] developed BP algorithm, namely multilayer feedforward network. BP algorithm includes signal forward propagation and error back propagation. This two-way feedback structure can reduce the error signal to the minimum at that time. In the 1990s, Vapnik et al. [13] proposed the SVM algorithm, that is, the concept of support vector machine. In 2006, Hinton et al. [14] alleviated the local optimal solution problem of ANN by using the pre training method. With the proposal of BP algorithm and SVM algorithm, the development of artificial neural network has become very rapid. At present, artificial neural network can be roughly divided into three levels, input layer, hidden layer and output layer [15]. The input layer receives external information and data, and the hidden layer is responsible for processing the information and constantly adjusting the connection attributes between neurons, such as weight, feedback, etc; The output layer is responsible for outputting the calculation results. Among them, the weight reflects the connection strength between units; Feedback reflects the positive and negative correlation between units. In the connection relationship between units, the information processing process is reflected through these information. Due to the unknown of the overall result, the weight and feedback in the hidden layer need to be continuously adjusted to finally achieve the best fitting result [16].

At present, the important models of artificial neural network are mainly divided into convolution artificial neural network model and recursive artificial neural network model. Convolutional neural networks (CNN) is a kind of neural network with multi-layer. It is a neural network with deep structure containing convolution calculation. The network is a trainable multi-layer network structure composed of two single-layer convolutional neural networks. It can integrate feature extraction, down sampling and traditional neural networks to form a new network. Compared with other neural networks, it can directly use the pixels of the image for pattern recognition, which effectively reduces the complex feature extraction and calculation process in the traditional recognition algorithm [17]. At the same time, convolutional neural network has good robustness to image translation, scaling and rotation. Recurrent neural network (RNN) is a real dynamic network system because there is feedback from output variables to input, so its variables include time-delay network [18]. Compared with static neural network, recursive network does not presuppose the order of the system in advance, which opens up a very promising field for the identification and control of dynamic systems. Because of its inherent feedback structure, dynamic recurrent neural network can better express a complex dynamic system and approach the dynamic process of the system with only a single-layer network. Because of its unique structure and information processing method, artificial neural network has obvious advantages in many aspects and has been widely used in various fields, such as robot navigation, natural earthquake prediction [19], intelligent control of high-speed communication network, soil surface pressure measurement [20], rotary deformation verification code recognition, chemical equipment fault diagnosis [21,22], process control and optimization [23-25], image recognition [26,27].

3. APPLICATION OF ARTIFICIAL NEURAL NETWORK IN RECTIFICATION

Although with the progress of science, people have more and more in-depth research on distillation column equipment, which has greatly improved the design level of distillation system. With the rapid development of computer technology, there are many industrial simulation software and design packages. The design optimization of distillation system is developing towards increasing production, saving energy, environmental protection and reducing cost. However, the parameter optimization method of distillation system is relatively backward, so more and more scholars devote themselves to the multi-objective parameter optimization of distillation system [28], and artificial neural network has become a very important multi-objective optimization method of distillation system because of its characteristics. At present, the commonly used artificial neural network ANN includes Hopfield network [29], high-order network, Self-organizing Artificial Neural Network [30], back propagation network, etc. Because the artificial neural network algorithm can approach any function in theory and has strong nonlinear mapping ability [31], it can better simulate and predict the complex reactive distillation process, so it can be used for the simulation and optimization of reactive distillation process. Wang et al. [32] used Ann and genetic algorithm to simulate and optimize the thermal coupling distillation process; Firstly, the adjustable variable is determined, and the change law of the optimized variable is determined and detected by training the sample data calculation of the neural network. Taking the separation of C5 component as an example, the process is simulated, and finally optimized by genetic algorithm [33]. It is obtained that the maximum relative error of reboiler load is 3.70%, and the relative errors of liquid phase side line recovery sb of main tower of product B and liquid phase side line recovery SC of main tower of product C are 1.04% and 1.60% respectively. It can be seen that ANN algorithm has high calculation accuracy, high solution efficiency and can effectively find the optimal operating conditions.

Artificial neural network can also be used to optimize the atmospheric distillation unit, which can greatly reduce the irreversibility of the system. Osuolale et al. [34] used bootstrap polymerization neural network (Bann) to optimize the atmospheric distillation unit (ADU) to predict the efficiency and product quality of ADU, so as to determine the optimal operating conditions of ADU. 2048 ANN data samples are generated from HYSYS (v8.2), in which the training data (50%) is used for network training, the test data (30%) is used for network structure selection (number of hidden neurons) and "early stop" in network training, and the unseen verification data (20%) is used to evaluate the finally developed neural network model. Fig. 1 shows the predicted and actual values of BANN.

If the predicted value and the actual value are superimposed on each other, it shows that the BANN model can almost perfectly imitate the training, test and verify the actual data. The optimization results show that when the weight of the minimum relative prediction error in the confidence interval is equal to 0.5, the efficiency can be increased by 76.71%, that is, the irreversible loss in the tower can be reduced by 44.8% and the energy cost can be reduced by 7.6%. This method can optimize the efficiency without affecting the product quality and process output, and can enhance the accuracy and reliability of the model. It is also of certain significance to optimize other systems.

In terms of energy-saving optimization of distillation system, Shi et al. [35] used BP neural network to optimize the energy-saving of methanol four tower distillation unit. They chose a three-layer neural network model with 7 inputs and 4 outputs, a total of 10 nodes. Select sigmoid as the hidden layer function and purelin as the input-output layer function [36]. Through Aspen simulation, the data used to train the weights of the neural network, that is, the capacity and energy consumption of the distillation column, are obtained [37]. Through the continuous training of this artificial neural network, the model of methanol four tower distillation process that can be used for optimization calculation is finally obtained. Based on the above, in one of the working conditions, the unit energy consumption after multi-objective optimization is reduced by 0.079kw/kg, and the output of refined methanol can be increased by 1472.4kg/h.

Wang et al. [38] took the solvent stock solution dichloromethane ethanol water mixture as the research material system, optimized the extractive distillation process with ethylene glycol as the extractant through BP neural network, created a BP neural network model [39], and selected the mass fraction of dichloromethane and the energy consumption of the tower as the objective function. An objective function is used, three parameters are input, and tansig [40] is used as the transfer function from input layer to hidden layer; trainbr is used as training function, with a total of 6 nodes, and purelin is used as the output function. After the mapping relationship is established, repeat the iteration until the error

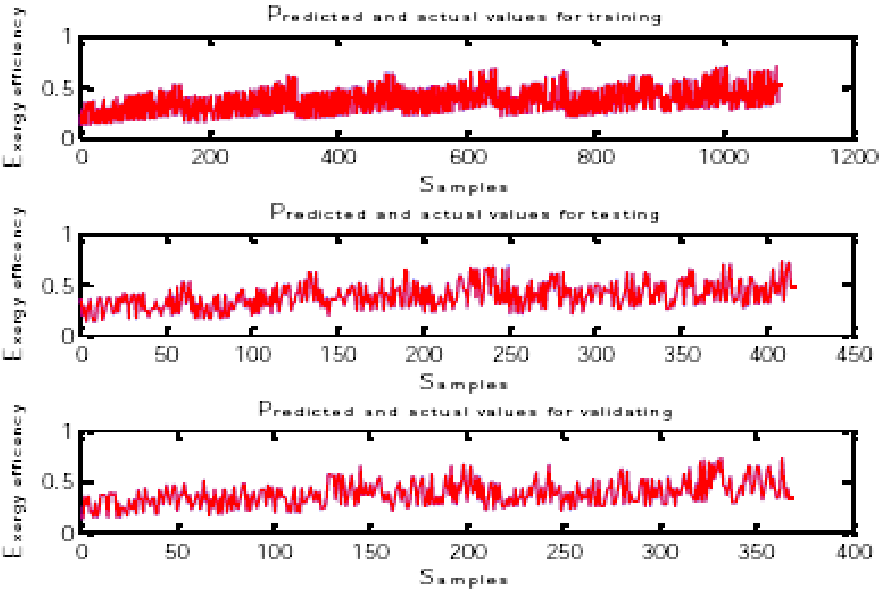

Fig. 1. The predicted and actual values of BANN [34]

descent gradient meets the requirements of prediction accuracy. After such optimization, it is predicted that the maximum dichloromethane content on the top of the tower can reach 98.85% and the minimum energy consumption of the tower kettle can reach 20.86kw. In fact, in actual production, the optimization results are different according to different objective functions and working conditions. When optimizing the energy saving of distillation system, we should pursue the two-way balance between product quality and reducing energy consumption to obtain the optimal operating conditions [41].

Fitriyani et al. [42] applied artificial neural network to establish the modeling of binary distillation column system, in which the feed volume, feed composition, heat load and reflux ratio of reboiler and condenser are taken as the input, the composition and flow of distillate and bottom product are taken as the output, and 80% training data and 20% verification data are used to obtain the correlation between the best standard error RMSE and the best coefficient between the prediction and set point value. Finally, the imperial competition algorithm (ICA) [43] is used to optimize Ann [44]. After optimization, the bottom product with molar flow equal to 252.0891 and molar fraction equal to 0.9932 is the best value. This shows that the nonlinear programming problem of distillation system can be effectively solved by using artificial neural network.

Based on the simulation of artificial neural network in reactive distillation [45], Feng Guohong [46] developed a new simulation method, that is, the artificial neural network trained by momentum BP algorithm with variable learning rate. The mature ANN is used to simulate the process of extractive distillation and reactive distillation. Taking the extractive distillation process of methanol and acetone and the reactive distillation process of esterification of methanol and acetic acid to produce methyl acetate as examples, the simulation calculation and analysis are carried out, Good results have been achieved. The extractive distillation and reactive distillation processes were simulated by CHEMCAD software [47]. In fact, when the target variable value is not greatly affected by the experimental error, it is feasible to simulate the extractive distillation process of methanol and acetone and the reactive distillation process of methanol and acetic acid esterification with CHEMCAD software, and the simulation results are in good agreement with the experimental results.

Tehlah et al. [48] used artificial neural network to simulate the process of refining palm oil and developed two different ANN models. One is an ANN model based on three inputs (F, t, P), and the other is an ANN model based on two inputs (T, P) (where f is the feed flow, t is the column temperature and P is the pressure). Different architectures are used to design feedforward and back propagation neural networks in Matlab toolbox. It can be found that ANN can accurately model the process of refining palm oil, and the prediction model is very close to the process predicted by Aspen HYSYS simulator. The results show that the optimal values of F, t and P are 1677kg / h, 142 ℃ and 0.00073kpa respectively. Under the optimal conditions based on this model, the nutrient recovery of the product can exceed 90%. This shows that ANN can well simulate complex distillation system, develop different ANN models, and then model and analyze the process, which has high accuracy.

4. CONCLUSION

After decades of development, artificial neural network has been relatively mature in some aspects and is slowly forming a perfect and comprehensive technology. Using the powerful tool of artificial neural network, people can carry out multi-objective optimization of the distillation system, obtain the optimal operation conditions of distillation with the advantages that traditional methods do not have, enable the industrial distillation tower to achieve a higher level of control, and further improve the economic benefits on the premise of ensuring the quality. In fact, although artificial neural network has been applied to all aspects of social production, as the precision of target control becomes higher and higher, people's research on artificial neural network technology will not stop.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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