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Research Progress of Chemical Process Control and Optimization Based on Neural Network

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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

Chemical process is usually regarded as a comprehensive system and optimized as a whole because of the interaction and restriction between its operation units. The classical control technology is limited to the control system dealing with single variable. Artificial neural network (ANN) is an algorithmic mathematical model that imitates the behavioral characteristics of animal neural networks for information processing. It has the advantages of nonlinear, large-scale, and strong parallel processing capabilities, as well as robustness. This article summarizes the basic principles and development history of ANN, and analyzes the research progress of chemical process control and optimization based on artificial neural networks in recent years.

Keywords: Artificial neural network; mathematical model; chemical process control; optimization.

1. INTRODUCTION

China has become the world's leading producer of petroleum and chemical products [1]. Chemical production is a complex process, which involves many equipment, complex processes, and high control difficulties. With the development of modern industry in the direction of large-scale and integrated development, the production process is becoming more and more complex. The severely nonlinear, time-varying, uncertain and strong coupling between variables make many systems unable to be accurately described by mathematical models; at the same time, industrial production the requirements for the overall performance of the process control

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are getting higher and higher, not only requiring the accuracy of the control, but also paying more attention to the robustness, real-time, fault-tolerant, and adaptive and self-learning capabilities of control parameters [2]. In addition, the shortage of raw materials and the continuous rise of energy prices, the increasingly fierce competition among enterprises, people have higher and higher requirements for improving production efficiency, improving product quality, reducing production costs, and strengthening environmental protection. Therefore, it is necessary to optimize the industrial production process and determine. It is very important to track the production process conditions and operating parameters that make the system run under the optimal conditions. However, it is difficult for traditional technologies to solve these problems in a short time. As an important part of artificial intelligence, artificial neural networks have been used more and more widely in the chemical industry due to their self-organization, self-adaptation, self-learning and other intelligent characteristics. Its emergence has greatly improved the technology and production environment in the chemical industry, and provided practical solutions to the problems that traditional technologies are difficult to deal with [3]. This article mainly provides a brief overview of artificial neural networks summarizes and analyzes the application research progress of artificial neural networks in chemical process control and optimization.

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural network is a nonlinear, adaptive information processing system composed of a large number of interconnected processing units. It is proposed on the basis of the results of modern neuroscience research. It attempts to process information by simulating the processing and memory information of the brain's neural network. That is, the artificial neural network is an information processing system designed to imitate the structure and function of the human brain [4]. Neural network technology simulates the nervous system. The processing unit is similar to the neural unit, and the computer control system is equivalent to the nerve center, analyzing data, processing data, and outputting results. The application of sensors provides a foundation for the development of neural networks. The neural network as shown in Figure 1 includes an input layer and an output layer, and several hidden layers. The role of the input layer is to accept external information and transmit information; the role of the output layer is to accept the information transmitted by the input layer, process information and feedback information; the role of the hidden layer is to combine and preprocess the information of the input layer. A series of processes of receiving, transmitting, processing and feedback of information make the neural network work. Due to the application of the processing unit, the neural network system is a self-learning, self-processing, and self-organizing intelligent system.

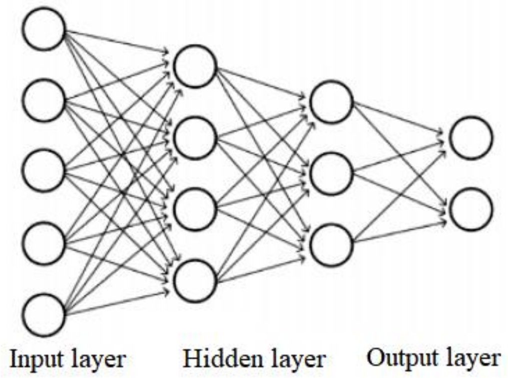

Fig. 1. The structure of Artificial neural network

Although the artificial neural network was proposed in 1943, it was not until the invention of deep learning technology in 2006 that it ushered in its true golden moment. [5].

In 1943, Mcculloch and Pitts [6] established a neural network and mathematical model called the MP model. They proposed a formal mathematical description of neurons and a network structure method through the MP model, which proved a single neuron can perform logical functions, thus ushering in the era of artificial neural network research. In 1949, Canadian psychologist Donald Olding Hebb[7] proposed the idea of variable synaptic connection strength, the well-known Hebb rule, which still plays an important role in various neural network models. In 1957, Frank Rosenblatt proposed a "perceptron" model, which is the world's first mathematical model with self-organization and self-learning capabilities [8]. The adaptive linear unit network proposed by Hoff in the early 1960s has also obtained good results in the research of adaptive systems, such as adaptive filtering, prediction and pattern recognition. During this period, the research of artificial neural network began to receive people's attention, the research work entered the initial period of prosperity, and the research of artificial neural network entered the first upsurge.

The neural network theory in the initial stage of development still had certain defects. At the same time, the artificial intelligence theory based on logical reasoning and the von Neumann-type computer were in their heyday of development, which covered it. The need to develop new intelligent computing theories and new intelligent technologies has brought the research of artificial neural network theory into a low ebb stage of slow development. It is marked by the publication of 《Perceptrons: an introduction to computational geometry》 by Marvin Minsky and Seymour Papert [9] in 1969. At the same time, the low computing power at the time could not support the amount of calculation required by the neural network model. One point of view caused a direct impact on the research of artificial neural networks at that time. In the following ten years, the research of artificial neural networks was at a low ebb [10]. In 1982, Hopfield proposed the Hopfield neural grid model, introduced the concept of "computational energy", and gave the network stability judgment [11]. In 1984, he proposed the continuous-time Hopfield neural network model, which made pioneering work for the research of neural computers, created a new way for neural networks to be used for associative memory and optimized calculations, and laid the foundation for neural computer research[12]. Hinton et al [13] proposed Boltzmann's model, using statistical thermodynamics simulated annealing technology in learning to ensure that the entire system tends to a global stable point. Rumelhart et al [14] developed the BP algorithm, which denied Minsky's erroneous conclusion on multilayer networks in 1969. The BP algorithm includes the forward propagation of the signal and the backward propagation of the error. This two-way feedback structure can reduce the error signal to the minimum at that time. At the same time, by adding a so-called hidden layer to the neural network, the back propagation algorithm also solves the XOR problem that the perceptron cannot solve. BP neural network model is the most widely used artificial neural network model in modern neural network as prediction [15,16].

In the early 1990s, the concepts of Support Vector Machines (SVM) and Vapnik-Chervonenkis (VC) dimensions were proposed by Vapnik et al [17-19]. Once SVM was invented, it reflected in several aspects. Advantages over artificial neural networks. SVM does not need to adjust the calculation parameters, and it obtains the global optimal solution, and its efficiency is much higher than that of neural networks. Therefore, it gradually replaces neural networks and becomes the mainstream operation model. However, at this time, the traditional neural network back propagation algorithm encountered an essential problem-vanishing gradient problem. As the number of layers of the neural network increases, the final output result has little effect on the parameters of the initial layers, and the training process of the entire network cannot convergence is guaranteed, that is, the solution of the equation obtained through the artificial neural network is not necessarily the optimal solution, and it may fall into the optimal solution within a certain range, rather than the optimal solution of the entire space. This makes the research of neural networks fall into a low ebb again during this period. After that, only a few scholars in the artificial intelligence community persisted in studying neural networks.

In 2006, Hinton et al[20] proposed the concept of "Deep Belief Networks" for the first time. They used the pre-training method to alleviate the local optimal solution problem of the artificial neural network, and set up 7 hidden layers, so that the artificial neural network has a real "depth" and set off a worldwide depth study the wave of research. In 2016, the emergence of AlphaGo brought people's research enthusiasm for deep learning to a new height. So far, artificial neural networks have been widely used in various fields, such as deep learning and game theory [21-23], process control and optimization [24-26], face recognition [27-29], forecasting [30-32], fault detection [33-35], image processing [36-38] and other fields [39,40]. The application of artificial neural network in the field of chemical process control and optimization will be reviewed below.

3. APPLICATION EXAMPLES OF ARTIFICIAL NEURAL NETWORK IN CHEMICAL PROCESS CONTROL AND OPTIMIZATION

With the continuous development of the chemical industry, the requirements for chemical process control are becoming increasingly stringent. Due to the uncertainty, nonlinearity, time delay, and strong coupling of multiple variables in the chemical control optimization process, conventional control systems sometimes appear to be inadequate, and the emergence of artificial neural networks makes the control and optimization results of various processes further improve [41-43]. In 1986, Rumelhart [14] first applied ANN to the field of process control. There are two ways to apply neural network for control: First, it is used to build a model, which mainly uses the prior information of the object, after error correction feedback, corrects the network weight, and finally obtains a causal function to realize state estimation, and then Inferential control; the other is directly as a controller for real-time control like a PID (Proportion Integration Differentiation) controller. Neural network is used for control, not only can handle precise knowledge, but also fuzzy information.

Optimal feedback control can in principle be obtained by solving the corresponding Hamilton-Jacobi-Bellman dynamic programming equation, though in general this is a difficult task. Edwards et al [44] proposed a practical and effective alternative for constructing an approximate optimal feedback controller in the form of a feed forward neural network. The controller is capable of approximately minimizing an arbitrary performance index for a nonlinear dynamical system for initial conditions arising from a nontrivial bounded subset of the state space. A direct training algorithm was proposed and several illustrative examples were given. Hussain[45] believed that the application of neural networks in the field of chemical process control is mainly in three aspects: predictive control, reverse model-based control and adaptive control. In the control process, the most commonly used neural network is the predictive control process. In the early reports on the predictive control process, Psichogios et al. [46] studied the application of artificial neural networks in control as process models and controllers, respectively. They compared internal model control (IMC) and multistep predictive control (MPC) when applied to control nonlinear SISO (Single Input Single Output) exothermic CSTRs (Continuous Stirring Tank Reactor). An IMC-type neural network controller was found to provide very good performance even when only partial state data is available. MPC-type neural controllers using the same neural network model and extending to include feedback also provide excellent performance. When a nonlinear network is used as the process model, the performance of both control techniques is significantly better than when the linear ARMAX (Exogenous autoregressive moving average) model is used.
Pei [47] aimed at the repeated iteration between the coordination layer and the local optimization layer of the large-scale industrial process decomposition and coordination method, and proposed a Hopfield network optimization method based on BP neural network modeling. The research results illustrate Hopfield neural network method can solve the steady-state optimization problem of industrial processes. Zhang et al[48] studied the typical nonlinear unit continuous stirring reactor CSTR in the chemical process, and proposed a neural network using a compensation fuzzy operator. The compensation learning algorithm can not only adjust the fuzzy membership function adaptively, but also dynamically Optimize the adaptive fuzzy rules, and the simulation experiments of different objects and process industry control show that it has better control performance than PID, and has stronger adaptability and better robustness than traditional FNN.

Song et al[49] studied the neural network as an adaptor to control the process of the bioreactor and obtained a good control effect. In 2004, Chen et al[50] proposed a dynamic optimization technology combined with a general dynamic matrix control algorithm neural network model, which optimizes the calculation performance and greatly reduces the calculation time. In 2009, Xia [51] chose generalized regression neural network and proposed a rotating generalized regression neural network based on the optimization of the structure parameters of particle swarm algorithm, and proved the effectiveness of the method through experimental simulations. In 2010, An Aimin[52] proposed a neural network model NMPC strategy based on the adaptive neural network weights of the improved differential evolution MDE method, which effectively improved the problems of inaccurate model prediction, poor real-time control and reduced control quality. In 2012, Arcotumapathy et al[53] used the golden section method to select the neural network architecture, constructed the neural network model, and studied the multi-factor and multi-objective optimization problem of catalyst design, and the results were accurate and robust.

In 2013, Cartwright et al [54] combined neural network with evolutionary algorithm for data analysis and dynamic process control of chemical process, which proved that the method is effective and reliable. In 2014, Ahmed [55] used BP feedback neural network to study the nonlinear relationship between input variables and control variables in CSTR, distillation tower and neutralization process, and verified through experiments that the use of neural network to control the process can be tracked the target process effectively, with low disturbance, faster feedback speed, and smaller average error. In 2016, Guo et al[56] used the fuzzy neural network of the BP network to perform PID control on the atmospheric and vacuum equipment, and selected the most complicated controlled object's decompression tower top temperature as the research object, and compared it with other control methods. The simulation results show that the use of fuzzy neural network control can improve the robustness of the pressure reduction tower top temperature cascade control system in the atmospheric and vacuum unit. In February of the same year, Ren et al[57] proposed a multi-modal neural network PID method on the basis of the BP neural network PID controller algorithm. Compared with the ordinary PID control method, the result showed that the method has strong adaptive ability and short transition time. Robustness is good, can improve the response speed, reduce the overshoot, and shorten the adjustment time. It makes up for the shortcomings of conventional PID control in the polymerizer control that the parameters are difficult to tune, the temperature control system is lagging, time-varying and non-linear. Huang et al [58] used a recurrent neural network to establish a model of the relationship between effluent quality and energy consumption in the sewage treatment process. Han et al [59] used the Lagrangian multiplier method to solve the optimization problem by constructing an optimization function, and used the Hopfield neural network to optimize the set values of dissolved oxygen concentration and nitrate nitrogen concentration, and achieved good results. NLJ algorithm is a random search method with variable shrinkage coefficient. Ma et al[60] used NLJ algorithm to optimize model identification parameters and filter parameters. Bi et al[61] used the NLJ algorithm to optimize the decision-making variables in the control of the distillation column and achieved good results.

4. CONCLUSIONS

In summary, the application of artificial neural networks in chemical process control and optimization has been relatively extensive and mature. After years of development, artificial neural networks have become an indispensable toolin the chemical process. However, people's understanding and research on biological nervous system are still not enough. The neuron network model used, both in structure and network scale, is a very simple simulation of the real neuron network. Most of the research results of neural networks have so far stopped at the stage of simulation or laboratory research . A complete and systematic theoretical system and a large number of difficult and challenging theoretical problems have not yet been resolved, and the actual successful applications also need to be further developed. Constantly enriching and accumulating theoretical levels, perfecting the technical reliability of artificial neural networks, and developing intelligent optimization control simulation software based on artificial neural networks will play a vital role in the future development of China's chemical industry. At the same time, the optimization of industrial processes has received more and more attention in today's society. The combination of neural network modeling and intelligent optimization algorithm optimization is also more and more widely used in the optimization of industrial processes. This is also an important research direction in the future.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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