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Research Progress of Artificial Neural Network and Its Application in Fault Diagnosis of Chemical Industry

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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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ABSTRACT

Many characteristics exhibited by artificial neural networks, such as nonlinearity, large scale, strong parallel processing ability, as well as robustness, fault tolerance, and strong self-learning ability, make it attractive for fault detection and diagnosis in complex systems. The relationship between the complex process, cumbersome process, and measurable process variable failure causes of chemical process is very complicated. Once a failure occurs, it will cause huge economic losses and casualties. The emergence of artificial neural network provides a new chemical fault diagnosis technology, which can carry out early and accurate fault detection and diagnosis for chemical process and equipment, so as to improve the efficiency and safety of production. This paper introduces the basic principle and development history of artificial neural network, as well as several typical artificial neural networks, such as back propagation algorithm (BP network), radial basis network (RBF network), and their application in chemical process fault diagnosis.

Keywords: Artificial neural network; fault diagnosis; chemical process; BP network; RBF network.

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1. INTRODUCTION

With the scale and complexity of chemical processes, various chemical accidents have become prominent problems in the entire industry. With the high complexity and danger of this industry, once the risks come, huge losses can be foreseen. Fault diagnosis and detection play a key role in industrial processes, avoiding safety issues and reducing overall product costs. However, in the complex chemical process, due to the large amount of monitoring data and the difficulty of fault diagnosis, the traditional fault diagnosis technology can no longer meet the actual needs. At present, the widely studied fault diagnosis models are mainly pattern recognition methods based on data analysis. Among the identification methods, artificial neural network (ANN) is the most commonly used [1]. “ANN is a suitable tool for fault detection and diagnosis, in which measurement data that cannot be identified at the moment of sensing are converted into useful decision-making information. The potential of this approach in chemical processes was originally proposed by Hoskins [2] and Venkatasubramanian” [3]. Watanabe et al. [4] demonstrated “the use of a two-stage neural network to add information about fault severity”. “A more detailed analysis of the learning, recall, and generalization properties of this method” is presented by Venkatasubramanian et al. [5]. Hoskins et al. [6] demonstrated “large-scale application to complex chemical plants. However, these methods are inherently static because neural networks are trained using only steady-state data. If steady-state operating conditions change, the network must be retrained to function properly. Often, faults need to be detected faster, and it is necessary to use transient data for this purpose”. Dietz et al. [7] developed “a method using moving temporal windows by presenting dynamic data and Li et al. [8] trained the network”. Ohga and Seki [9] used multiple sets of time series data to train the network. Artificial neural networks can diagnose faults through their ability to learn and generalize nonlinear relationships. Artificial neural networks can store information about historical failures, and then associate and remember them. In predictive mode, when an operational process provides a new set of data, a trained neural network can classify it and provide stable, highly sensitive fault diagnosis. This paper mainly gives a brief overview of the concept and development of artificial neural network, and introduces the application of several typical neural networks in chemical faults, such as back propagation (BP network) neural network [10,11] is widely used for fault diagnosis in chemical process, especially for multi-fault and multi-signal pattern recognition problems, radial basis network (RBF network) can approximate any nonlinear function, can deal with the unanalyzable regularity in the system, and has good generalization (Fig.1,2). It has fast learning and convergence speed, and is suitable for fault diagnosis of chemical process.

2. ARTIFICIAL NEURAL NETWORKS

2.1 Characteristics and Structure Characteristics of Artificial Neural Network

“Artificial Neural Networks (ANNs) have been a hot topic in the field of artificial intelligence since the 1980s. It abstracts the neural network of the human brain from the perspective of information processing, establishes a simple model, and forms different networks according to different connections” [12]. “Try to simulate the neural network processing of the brain and memorize information in the way of information processing. A neural network is a computational model that consists of a large number of nodes (or neurons) interconnected” [13,14]. “Each node represents a specific output function, called the activation function. The connection node between each two represents the weight of the signal passing through the connection, called the weight, which is equivalent to the memory of the artificial neural network” [15,16]. “The output of the network will vary depending on how the network is connected, the weight values, and the excitation function. However, the network itself is usually an approximation of some algorithm or function, or it may be an expression of a logical policy” [17]. “In an artificial neural network, a neuron processing unit can represent different objects, such as features, letters, concepts, or some meaningful abstract pattern” [18]. “The types of processing units in the network fall into three categories: input units, output units, and hidden units. The input unit accepts signals and data from the outside world” [19]. “The output unit realizes the output of the system processing result. Hidden units are units located between the input and output units and cannot be observed outside the system” [20]. “Connection weights between neurons reflect the strength of connections between cells. The representation and processing of information is embodied in the connection relationship of the network processing units. Artificial neural network is a non-procedural, adaptive, brain-type information processing, and its essence is a parallel distributed information processing function through network transformation and dynamic behavior, and imitates human's brain and nerves carry out information processing systems" [21,22]. "It touches various fields of neuroscience, mind science, artificial intelligence, computer science and other interdisciplinary fields" [23-27]. "Artificial neural network is a parallel distributed system, which adopts a completely different mechanism from traditional artificial intelligence and information processing technology, overcomes the shortcomings of traditional logic-based artificial intelligence in processing intuition and unstructured information, and has adaptive, self-organizing and real-time learning features" [28].

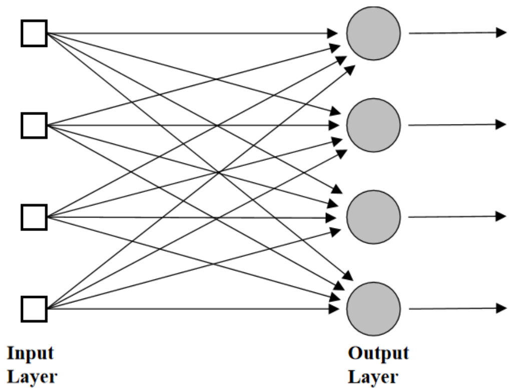

Fig. 1. Artificial Neural Network

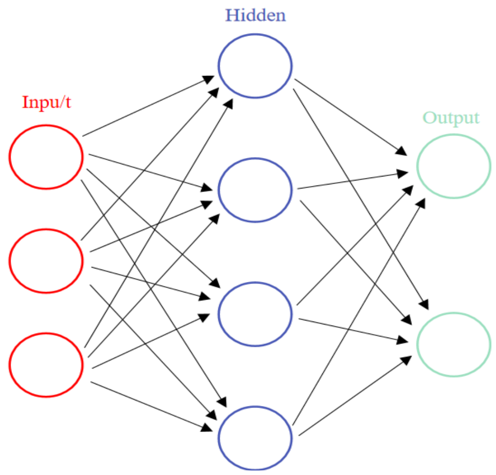

Fig. 2. Input and output of artificial neural network

2.2 The Origin and Research Progress of Artificial Neural Network

The development process of artificial neural network can be roughly divided into four stages, namely the rising stage, the ebb stage, the revival stage, and the prosperity stage.

"In 1943, American psychologist Mcculloch and mathematician Pitts [29] proposed the M-P model, which is a simple but significant model. In the model, the algorithm is realized by treating neurons as functional logic devices, thus starting the theoretical study of neural network models". In 1949, the psychologist Herb [30] published "The Organization of Behavior" and put forward the hypothesis that the strength of synaptic connections is variable. This hypothesis suggests that the learning process ultimately occurs at the synaptic interface between neurons, and that the strength of synaptic connections varies with the activity of pre- and post-synaptic neurons. This assumption evolved into the famous Hebb rule in neural networks. This law tells people that the strength of synaptic connections is variable between neurons, and this variability is the basis of learning and memory. Hebb's law lays the foundation for building neural network models with learning capabilities. In 1957, Rosenblatt [31] proposed "the Perceptron model based on the M-P model. The perceptron model has the basic principles of modern neural networks, and its structure is very neurophysiological. This is an MP neural network model with continuously adjustable weights. After training, the purpose of classifying and identifying a certain input vector pattern can be achieved". Although relatively simple, it was the first true neural network. Rosenblatt demonstrated that a two-layer sensor can classify input, and he also proposed an important research direction for a three-layer sensor with hidden layer processing elements. Rosenblatt's neural network model contains some basic principles of modern neural computers, forming a major breakthrough in neural network methods and technologies. In 1959, the famous American engineers B. Widrow and M. Hoff and others proposed "the neural network training method of adaptive linear element and Widrow-Hoff learning rule, and applied it to practical projects, becoming the first to solve practical problems. Artificial neural network, promote the application and development of neural network research. The ADALINE network model is a continuous-valued adaptive linear neuron network model that can be used in adaptive systems".

"Minsky and Papert, one of the founders of artificial intelligence, conducted mathematical research on the functions and limitations of network systems represented by perceptrons. In

1969, he published a blockbuster book, The Perceptron, pointing out that simple linear perception has limited capabilities" [32]. "It cannot solve the classification problem of two classes of linearly inseparable samples. For example, a simple linear sensor cannot implement XOR logic. This conclusion brought a heavy blow to the artificial neural network of the time. In the history of neural networks began a 10-year low point" [32]. In 1972, Professor Kohonen T of Finland proposed the self-organizing feature map. Later neural networks were mainly based on the work of Kohonen T. The SOM network is a tutor learning network mainly used for pattern recognition, speech recognition and classification problems. It employs a "winner is king" competitive learning algorithm, which is very different from the previously proposed perceptron. At the same time, its learning and training method is a self-organizing network, without the need for guided training. This learning and training method is often used as a training method to extract classification information without knowing what classifications exist. In 1976, Professor Grossberg proposed "the famous adaptive resonance theory, which has the characteristics of self-organization and self-stabilization".

"In 1982, American physicist Hopfield [33] proposed discrete neural network, namely discrete Hopfield network, which strongly promoted the research of neural network. In the network, Lyapunov function was introduced for the first time. Later researchers also called the Lyapunov function an energy function to prove the stability of the network. In 1984, Hopfield proposed a continuous neural network, which changed the activation function of neurons in the network from discrete to continuous". In 1985, Hopfield and Tank solved "the famous traveling salesman problem using Hopfield neural networks. Hopfield neural network is a set of nonlinear differential equations. Hopfield's model not only provides a nonlinear mathematical generalization of the information storage and retrieval functions of artificial neural networks, but also provides dynamic equations and learning equations. It also provides important formulas and parameters for network algorithms, enabling the construction and learning of artificial neural networks to have theories under the influence of the Hopfield model". A large number of scholars have stimulated the enthusiasm for studying neural networks and actively devoted themselves to this academic field. Due to the great potential of Hopfield neural network in many aspects, people pay more attention to the research of neural network. More and more people began to study neural networks, which greatly promoted the development of neural networks. In 1983, Kirkpatrick et al. Realize that "simulated annealing algorithms can be used to solve NP-complete combinatorial optimization problems". "The method of simulating the annealing process of high temperature objects to find the global optimal solution" was first proposed by Metropli et al. in 1953. In 1984, Hinton cooperated with young scholars Sejnowski et al., proposed "a massively parallel online learning machine, and explicitly proposed the concept of hidden units, which is the later Boltzmann machine". Using concepts from statistical physics and methods, Hinton and Sejnowsky first proposed a multi-layer network learning algorithm known as the Boltzmann machine model. In 1986, D.E. Rumelhart et al. proposed "the back-propagation algorithm BP algorithm based on the multi-layer neural network model to solve the weight correction problem of the multi-layer neural network". The learning problem of the forward neural network proved that the multi-layer neural network has strong learning ability, it can complete many learning tasks and solve many practical problems. In 1988, Chua and Yang proposed "the cellular neural network model, a large-scale nonlinear computer simulation system for cellular automata. Kosko builds a bidirectional associative storage model with unsupervised learning capabilities". In 1991, Haken introduced "synergy into neural networks, and in his theoretical framework, Haken considered cognitive processes to be spontaneous assertions that pattern recognition processes are processes of pattern formation". In 1994, Liao Xiaoxin proposed "the mathematical theory and foundation of cellular neural network, which made new progress in this field. By broadening the activation function categories of neural networks, more general delayed cellular neural networks, Hopfield neural networks and bidirectional associative memory networks are given. After years of development, hundreds of neural network models have been proposed".

In 2006, Hinton et al. [34] proposed "deep learning, which is a new field of machine learning. In essence, deep learning is to build a machine learning architecture model with multiple hidden layers, and obtain a large number of more representative feature information through large-scale data training. The deep learning algorithm breaks the limitation of the number of layers of the traditional neural network, and the designer can choose the number of network layers according to their needs".

3. APPLICATION OF ARTIFICIAL NEURAL NETWORK IN FAULT DIAGNOSIS OF CHEMICAL PROCESS

There are various links involved in chemical production. When a link fails, if it is not handled in time, it will paralyze this link or even paralyze the entire production process, resulting in major safety accidents. An efficient, real-time, and predictive system for detecting and diagnosing faults is the guarantee of safe and efficient production in chemical process control. Neural network system is a bionic system, a dynamic system with thinking, consciousness and learning ability, which can deal with complex things and environments, continuously correct the system according to the actual production process, monitor changes in parameters in real time, and diagnose and alarm faults. At present, the main types of neural networks for fault diagnosis are: back propagation algorithm (BP network), radial basis (RBF) network, adaptive network and so on. RBF network is superior to BP network in terms of approximation ability, classification ability and learning speed. At present, radial basis network is more and more used in fault diagnosis research [35].

Fault diagnosis is the most valuable field of artificial neural networks for the following three reasons [36]:

1) by training artificial neural networks, relevant process knowledge can be formed and stored and directly learned from quantitative historical fault information;
2) The artificial neural network has the ability to filter out noise and draw conclusions in the case of noise, making the artificial neural network suitable for online fault diagnosis and detection;
3) The artificial neural network has the ability to distinguish the cause and fault type.

3.1 Application of BP Network in Fault Diagnosis of Chemical Process

BP neural network is a multi-layer forward network with one-way propagation. BP network is widely used in fault diagnosis of chemical process, and has good robustness, fault tolerance and self-learning ability. Venkatasubramanian et al. [3] first proposed the application of BP network to fault diagnosis of chemical process, and proved the potential of this method with the aid of a case study of a refinery in the fluidized catalytic cracking process. The system based on BP neural network successfully diagnosed the training glitches. Later, some experts and scholars applied the BP network and its improved method to the fault detection and diagnosis of chemical process [37,38]. Huang Dao et al. [39] used three BP models to diagnose faults in the TE process, namely the standard BP algorithm, the improved BP algorithm and the L-M (Levenberg-Marquardt) method to optimize the BP network first, among which the L-M method has the best effect. The improved BP model has a good diagnostic effect in the actual industry, has stronger learning and generalization ability, and can overcome the shortcomings of traditional BP network such as slow convergence and easy to fall into local minima. In the research carried out by Miao Suyun et al. [40], the "BP neural network and the probabilistic neural network were combined, and then the TE process was used for fault diagnosis verification".

3.2 Application of RBF network in fault diagnosis of chemical process

RBF network can approximate any nonlinear function, can deal with the regularity that is difficult to analyze in the system, has good generalization ability, and has a fast learning convergence speed, which is suitable for fault diagnosis of chemical process. In 1992, Leonard and Kramer [41] and others proposed a new radial bias function network for fault diagnosis. They replaced the Sigmoid function with a Gaussian density function in the first hidden layer of the network, and successfully solved the problem of coexisting faults. Gu Lei [42] and others proposed to apply a probabilistic neural network (PNN), an important variant of RBF network, to fault detection in chemical processes. The probabilistic neural network is used in the simulation experiment of Tennessee Eastman (TE) process fault detection. The simulation results show that the number of training samples required by the probabilistic neural network is less than that of the BP network, the network structure is more complex than that of the BP network, and the fault detection of the probabilistic neural network is the accuracy rate is significantly higher than that of the BP network, and the design time of the neural network is significantly less than that of the BP network. Compared with other networks, the biggest advantage of probabilistic neural network is that the initial weight does not need to be set, only the input vector and output vector need to be determined. Shi Dongyuan et al. [43] combined RBF neural network and fuzzy integral for fault diagnosis of large power grids, which made up for the shortcomings and deficiencies of existing methods in tie-line fault diagnosis, and the fusion of the two methods has strong robustness.

Sawattanakit and Jaovisidha [44] used “an RBF network as an online approximator for process fault detection and diagnosis in a continuous stirred tank reactor (CSTR)”. The advantage of this idea is that no training data is required. But a system model is necessary. The simulation results in the literature are as follows:

3.2.1 Full state measurable case

All single and double faults can be detected and diagnosed within 30-40 minutes, while the equipment stabilization time is about 3 hours. Fig. 3 shows the faults estimated by the online approximator at t=12 with faults#1n 5% and faults#3p 5%.

Untestable concentrated cases: all single faults and most double faults can be correctly detected and diagnosed within the factory settling time. Fig. 4 shows the estimated failures from the online approximator at t=12 with failure#1n 5% and failure#3p 5%.

Simulation results show that it is measurable in the full state. Process faults can be detected and diagnosed during transients. However, in a situation where a state is unmeasurable, the unmeasurable state should be estimated before a process failure can be detected and diagnosed. In the latter case, the final result can only be done after a certain period of time required for stabilization time has elapsed.

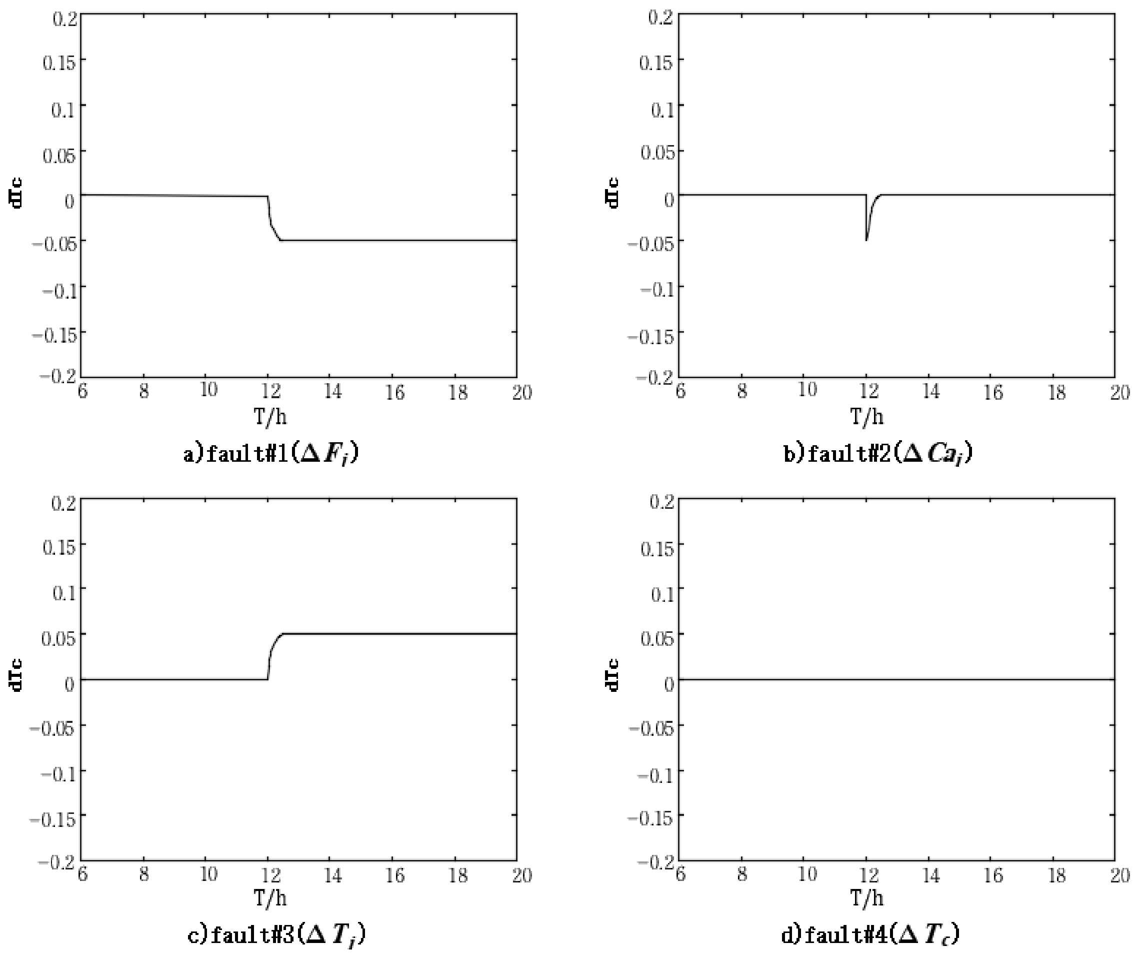

Fig. 3. Estimated failures of failure#1n 5% and failure#3p 5% at t=12 with full state measurable

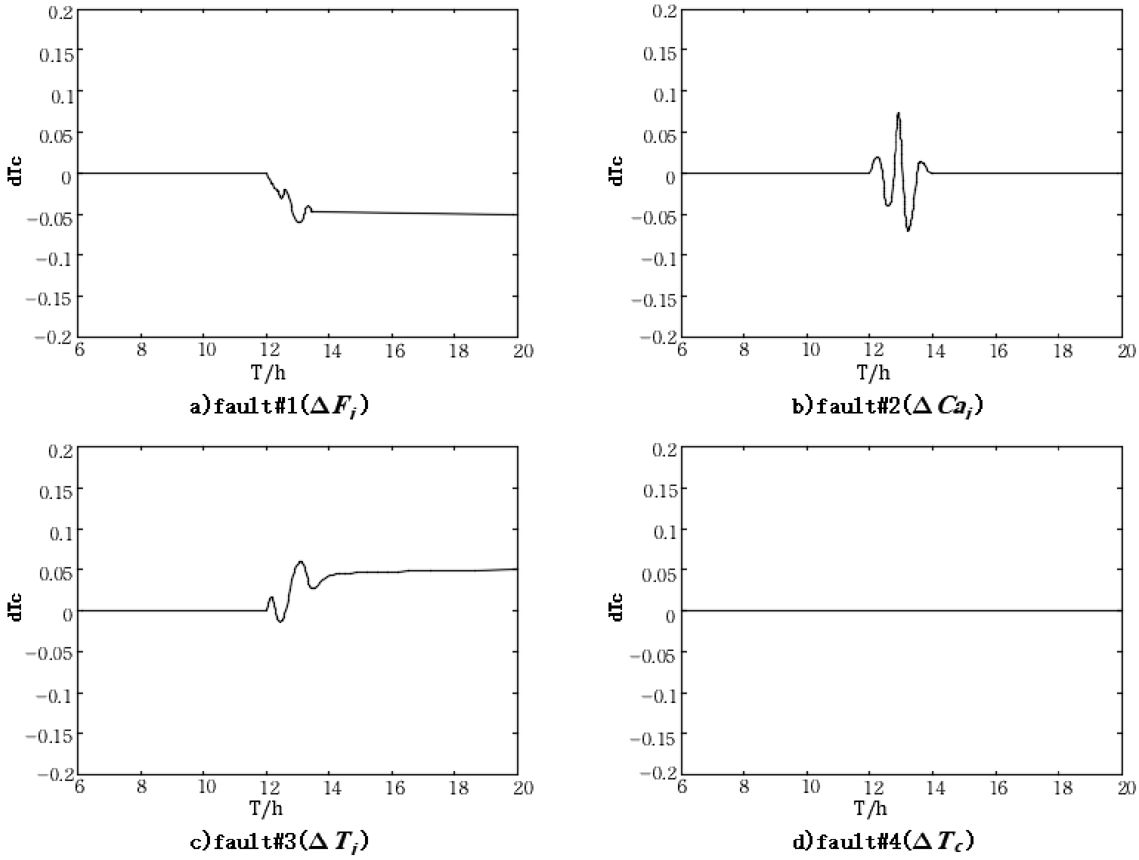

Fig. 4. Estimated failure at t=12 with failure#1n 5% and failure#3p 5%

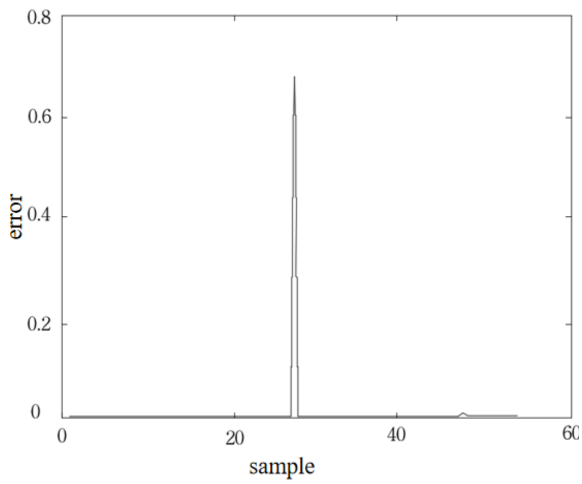

Fig. 5. Test error of BP network

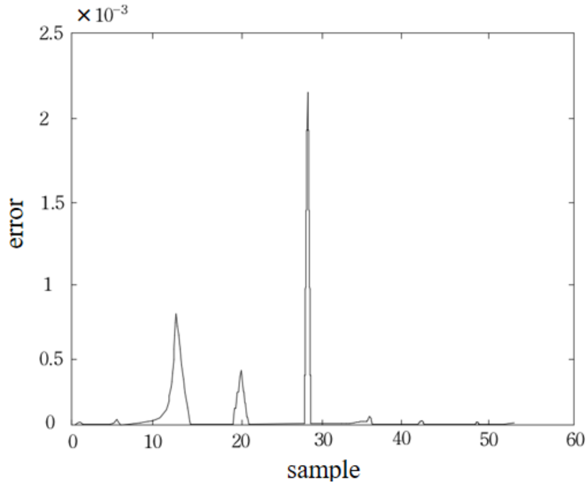

Fig. 6. Test error of ACO-BP network

3.3 Application of Other Neural Networks in Chemical Fault Diagnosis

Because the convergence behavior of the BP algorithm depends largely on the choice of network connection weights and threshold initial values, there are certain limitations in fault detection, Chen JX [45] analyzed “the faults of continuous stirred tank reactors (CSTR) by Type, the ACO algorithm is introduced into the neural network training, and the chemical process fault diagnosis is realized based on the ACO-BP algorithm, and the results are compared with the traditional BP algorithm”. ACO-BP network adopts a new algorithm called ACO-BP hybrid algorithm in ACO-BP neural network by combining ACO with BP. The main idea of this hybrid algorithm is to use the ACO algorithm to train all the weights and thresholds of the BP network, and to find the optimal initial weights and thresholds of the BP network by minimizing the training error norm. Finally, the BP algorithm is used to search for the global optimal value. In this way, this hybrid algorithm can find the optimal value faster. The following is the comparison result of the performance and fault diagnosis error of the ACO-BP algorithm and the traditional BP algorithm in the experiment.

Fig. 5 above show the performance and test error of the BP network with random initial weights and thresholds, respectively. Fig. 6 above show the performance and test error of the ACO-BP network with optimal initial weights and thresholds, respectively. Through the combination of ACO algorithm and BP algorithm, the generalization ability and diagnosis accuracy of the network are improved. The error norm of training samples is reduced from 0.0132 to 0.001, and the error norm of test samples is reduced from 0.7215 to 0.0016, and the diagnostic accuracy based on ACO-BP network is 100%. The experimental results show that the ACO-BP network can obtain better fault diagnosis accuracy than the traditional BP network in CSTR fault diagnosis.

Sorsa et al. [46] studied “a real heat exchanger continuous stirred tank reactor system as a test case. The system has 14 noise measurements and 10 failure case studies. Visualize the arrangement of different failure categories with the main component analysis”. Using three different neural networks: a multilayer perceptron network, a self-organizing neural network, and an adaptive resonance network, for fault detection and diagnosis of process measurement-based classification, the effectiveness of the three networks is demonstrated. Tang et al. [47] took the Tennessee Eastman(TE) process as the object, firstly classified the TE process faults through prior knowledge and then extracted variables related to the fault type; A neural network is used for the complete fault diagnosis process; the final result shows that the chemical process fault diagnosis model based on prior knowledge and multi-neural network has a better diagnosis effect. In 2010, Reza [48] applied “the hierarchical artificial neural network to the chemical process, and compared the method with the traditional single neural network and dynamic principal component analysis method. two other methods”. Mahdieh Askarian et al. [49] proposed “a fault diagnosis framework based on Bayesian Networks(BN). This probabilistic approach can directly involve non-uniform probability distributions of faults and non-Gaussian probability distributions of features”. Xavier et al. [50] proposed “a new method for fault detection and diagnosis in chemical process based on long and short-term memory network”. Zhang Weihua [51] proposed “a hybrid fault diagnosis algorithm of neural network + SDG, which can greatly improve the efficiency of fault diagnosis”.

4. CONCLUSION

To sum up, the development process of artificial neural network is bumpy. So far, most of its research results have stopped at the stage of simulation or laboratory research, the theoretical system of the complete system has not been established, and there are still many complex theoretical problems that have not been solved. However, because of some excellent characteristics of artificial neural network, it has been widely used in the process of chemical fault diagnosis, and also achieved good results, improving the efficiency of diagnosis. At present, the application of artificial neural network in various fields is developing in the direction of artificial intelligence. Neural networks will go a step further in future research on chemical fault detection.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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