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Application of Artificial Neural Networks for Chemical Industry Safety Production: A Review

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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 industry as a national pillar industry, safety management is particularly important; Safety assessment is the use of relevant technologies to assess the risks in the production process of a company. The key is the selection of evaluation methods and means, which can directly influence the effect of the evaluation. However, since the object of chemical safety production evaluation is influenced by many factors, it is concerned with a non-linear relationship between cause and effect. Artificial neural network can make use of the threshold value between neuron nodes and the connection weight value between nodes based on artificial function to carry out non-linear mapping input and output in advance, which has obvious advantages in dealing with non-linear complex problems.

Keywords: Chemical production; artificial neural network (ANN); safety evaluation.

1. INTRODUCTION

As an important enterprise of the world economy, for a long time, the chemical industry has played an essential role in our country's national economic development. Because of the unique characteristics of the chemical industry, its production process is a high-risk operation, with toxic and hazardous, flammable, explosive and other dangerous features, industry safety issues are notable [1]. Emphasis on safety evaluation and the establishment of the chemical enterprise safety production evaluation system is an important guarantee for the safety production of

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chemical enterprises. A chemical industry safety evaluation model was constructed by an artificial neural network, which has certain guiding significance for safety production management, improves the quality of safety evaluation of chemical enterprises, ensures safe production, strengthens hazard prevention, reduces the probability of accidents, and reduces property losses and casualties, which has a positive and significant effect [2-4].

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks, like other machine learning methods, have been used to solve various problems in production and practical applications, such as process control and optimization [5-7], image recognition and single processing [8-10], forecasting [11,12], traditional Chinese medicine processing [13-15], aquatic products [16,17], security risk assessment [18,19], intelligent driving [20-22], and so on [23-26].

2.1 Basic Principles

Artificial neural network is a non-linear, self-organizing and adaptive system, which includes a number of units. It has a research hotspot that has emerged in the field of artificial intelligence since the 1980s, trying to simulate the way neural networks process and remember information and design a new machine with human brain-style information processing capabilities [27,28].

The complete algorithm structure of traditional ANN is composed of at least three different layers: input layer, hidden layer and output layer (Fig. 1). [29,30].

Under the appropriate activation function, the optimized combination of weights can generate predictions for the dependent variable:

$$NET = \sum_{i,j}^{n} w_{i,j} x_i + b \tag{1}$$

$$y = f(NET) \tag{2}$$

Where $w_{i,j}$ represents the weight value, x_i represents an inputted independent variable (or outputs from the previous layer), and b represents a bias, or threshold, f represents the activation function, such as proportional function, quadratic function, hyperbolic function, m -type function, Y -type function, etc. This model is called the McCulloch-Pitts Model, also known as a processing element of the neural network [31-33].

2.2 Basic Characteristics

There are a large number of processing units in an artificial neural network which is a nonlinear adaptive information processing. The elimination of this system is established on the basis of modern neuroscientific findings, through neural network processing, to simulate information through the memory information of the brain. Mainly have the following characteristics:

Non-linearity is a common feature in nature. Non-linear phenomena are like the wisdom of the brain. The neural network has better performance, can greatly improve the storage capacity of the network, and reduce the fault tolerance of the network [34,35].

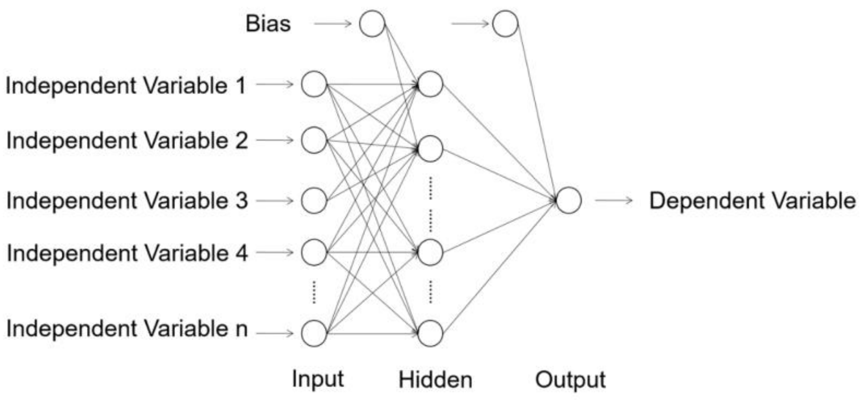


Fig. 1. A typical structure of artificial neural network (ANN)

Non-limiting, artificial neural networks usually consist of many neurons. The characteristics of a single neuron can determine the behavior of the entire system, and it also depends on the results of the interaction between the units. Simulate the brain through the connections between units, a typical example is an associative memory [36].

Non-constant qualitative, the information processed by the neural network and the nonlinear dynamic system is not static but constantly changing [37].

Non-convexity, usually refers to a specific state function, under certain conditions, affects the evolution direction of a non-convex system. For example, the relative steady state of the system corresponds to the extreme value of the energy function. A non-convex function means that it has multiple extreme values. Therefore, the system has multiple stable equilibrium states, which causes the system to evolve into diversity [38].

2.3 Classification

Artificial neural network can be divided into feedback network and feedforward network in terms of structure [39].

Feedforward network: The network information advances layer by layer from the input layer to the hidden layers, then to the output layer and final output.

Feedback network: all of the nodes in the feedback network have information processing functions, and each node can receive input and output at the same time.

2.3.1 Feedforward neural network

Feedforward neural networks, the simplest type of neural network, have neurons arranged in layers, with each neuron connected only to neurons in the previous layer. The output of the previous layer is received and output to the next layer, and there is no feedback between the layers. As shown in Fig. 1, it is one of the most widely used and rapidly developing artificial neural networks [4, 40].

2.3.2 Feedback neural network

Feedback neural network, also known as recursive network and regression network, is a neural network system that connects the output to the input layer after a step time shift. In this type of network, neurons can be interconnected, and the output of some neurons will be fed back to neurons in the same layer or even the previous layer. The common ones are Hopfield neural network, Elman neural network, Boltzmann machine, etc. [41].

2.3.3 The main difference

(1) There is no connection between the neurons in each layer of the feedforward neural network. The neurons only accept the data from the upper layer, and then pass it to the next layer after processing. The data flows forward; the neurons between the layers of the feedback neural network are connected, and the data can flow between the same layers or feedback to the front layer.
(2) The feedforward neural network does not consider the time lag effect of output and input, and only expresses the mapping relationship between output and input; The feedback neural network considers the time delay between output and input, and needs to use dynamic equations to describe the model of the system.
(3) The learning of feedforward neural network mainly adopts error correction method (such as BP algorithm), the calculation process is generally slow, and the convergence speed is relatively slow; the feedback neural network mainly adopts Hebb learning rules, and the calculation convergence speed is generally fast.
(4) Compared with feedforward neural networks, feedback neural networks are more suitable for applications in associative memory and optimized calculations [42-44].

2.4 Learning Rules

Learning is the process by which individuals are trained to produce more lasting changes in their behavior, and generally the effect increases with training, i.e., progress is gained through learning.

2.4.1 Supervised learning

The learning model of supervised learning is error correction. The actual output of the ANN is compared with the desired output, and when it does not match, the weight parameters are adjusted according to certain rules and recalculated and compared until the network is able to produce the desired output for the given

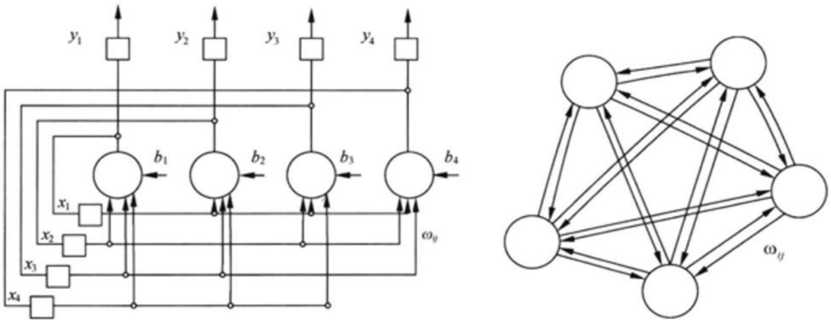


Fig. 2. Feedback neural network

input, then the network is considered to be trained, i.e., it has learned the knowledge and rules in the sample data. It can then be used to solve practical problems.

2.4.2 Unsupervised learning

The learning mode of unsupervised learning is self-organizing, learning regardless of the dynamic input information given to the network, Unsupervised learning is a training method that is essentially a statistical tool to discover underlying structures in unlabeled data. It has 3 main features: unsupervised learning has no explicit purpose; unsupervised learning does not require labeling the data; unsupervised learning cannot quantify the effect.

2.4.3 Indoctrination learning

The learning mode of indoctrination learning is rote learning, where the network is designed to memorize a particular example, and the network can recall the example when the input is that example. The network weights are not obtained by training, but by some design method. Once the weights are designed, they are instilled into the network once and never changed again.

3. SAFETY EVALUATION

As an important basic industry of the national economy, the chemical industry contains tens of thousands of product types, each with different physical and chemical properties. As a pillar industry, the chemical industry plays an important role in the world economy. The chemical industry also has a huge role in electronics, home building materials, textiles, equipment manufacturing, agriculture, aerospace and other industries. The consumption of chemical products is very closely linked with the national economy, and the main destinations are widely distributed in various fields of the national economy, such as infrastructure, real estate, agriculture, automobiles and garments, etc. Along with the way of economic growth driven by fixed asset investment becoming limited, the development of the domestic economy has entered a new stage. A comprehensive safety evaluation of the chemical industry production status systems is required, which involves complex situations and many demand factors, the main traditional linear evaluation methods are risk matrix analysis (LS), operating conditions hazard analysis (LEC), method of risk level analysis (MES) [45,46].

3.1 Risk Matrix Analysis (LS)

Risk matrix analysis, R = L × S, where L is the likelihood that the risk event will occur; S is the potential impact of the consequences of the accident; R is the combination of the possibility of an accident and the consequences of the event, the larger the R value, the greater the danger and risk of the system.

3.2 Operating Conditions Hazard Analysis (LEC)

L (likelihood, the possibility of accidents), E (exposure, the frequency of personnel exposure to hazardous environments) and C (consequence, once the accident may cause the consequences). Determine different scores for different levels of the three factors, and then use the product of the three scores D (danger, danger) to evaluate the size of the dangerous operating conditions, that is: D = L × E × C. The greater the value of D, indicating that the operation activities are dangerous and risky.

3.3 Method of Risk Level Analysis (MES)

People often express the magnitude of the likelihood L and the severity of the consequences S in terms of values indicating the relative gap, respectively, and then use the product of the two to reflect the magnitude of the degree of risk R, that is, R = LS = MES. (The state of control measures M, the frequency of human exposure or hazardous state E) [47].

4. APPLICATION ADVANTAGES

4.1 BP Neural Network Structure in the Design of Evaluation System

Taking the BP neural network structure as an example, the embodiment of the BP neural network model is realized through the design of the evaluation system. It is the most commonly used neural network topology. The BP network model is composed of four models: self-training model, calculation error model, transfer function model and input-output model. Mainly used in security system evaluation: first determine the hidden layer, output layer and input layer of the neural network, the number of nodes, the structure level, and the topological structure to make the information specific. The neural network is associated with the relevant parameters in the safety management evaluation system, and the corresponding relationship with the topological structure is established, such as the type, quantity and characteristics of the parameters related to the neural network and the safety evaluation system, and the expression mode management evaluation system and various characteristics of the system are determined. Select learning samples to provide neural networks for training, try to collect comprehensive samples, the more samples they have, the more comprehensive they will learn about neural networks. Try to select multiple samples and be representative. In the safety production process of the enterprise, it is also based on their own safety status. Below, represented by the sample, the training process of the sample is actually a process of weight correction and error reduction between network nodes [48,49].

According to the analysis and investigation of the safety situation of chemical enterprises, it is determined that there are 4 major aspects, which affect the safety of chemical industry, including nearly all aspects in the chemical industries, as shown in Table 1.

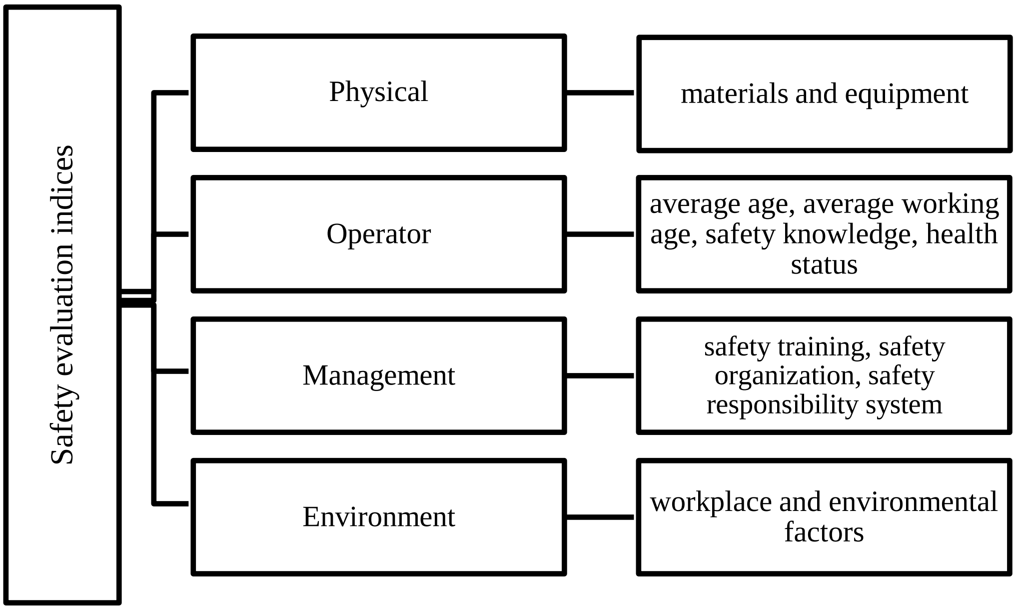
1. Physical: Safety of toxic chemicals and high pressure and high temperature chemical equipment, etc.
2. Operator: The quality of production personnel has a very crucial control on the system of the safety evaluation. The main factors are education, age, work experience, psychological quality, education and training process, health status, etc.
3. Management: Including safety training, safety responsibility system, security check etc.
4. Environment: the environmental and workplace factors. such as chemical production area, safe production distance, warning line, temperature, atmospheric humidity, light and lighting intensity, etc.

4.2 Advantages of Artificial Neural Network in the Safety Evaluation

(1) Overcoming the shortcomings of traditional safety evaluation methods makes the results more reasonable. When we use the traditional linear method for chemical safety production evaluation, it is necessary to compile various checklists and develop evaluation standards in advance. The assessor must have a wealth of practical experience and knowledge. The safety evaluation process is easily influenced by the subjective factors of the evaluators, which leads to non-objective and unscientific evaluation results. The optimization and control of the selected independent variables make the safety evaluation results more scientific by virtue of the properties of artificial neural networks based on system theory.

(2) Artificial neural network which conforms to a nonlinear functional relationship establishes the chemical safety production evaluation model. LS, LEC, and MES all use simple linear functions to analyze security problems. But the chemical production safety evaluation is a very large system with amounts of influencing things and large uncertainties. The relationship between production problems and production safety evaluation system is a very complex nonlinear function. Artificial neural network fits this characteristic well, so we can choose a nonlinear function to build the safety production model [50,51].

Table 1. Chemical industry safety evaluation of artificial neural network



5. CONCLUSION

As a pillar industry of the country, the chemical industry carries the great responsibility of economic development and plays a decisive role in improving national income and meeting people's pursuit of a better life. Due to the high risk of the chemical industry, once it happens, it will lead to serious loss of life and property. The drawbacks of traditional linear safety production assessment aspects are presented more and more with the development of the times, and it is urgent to adopt a new artificial neural network nonlinear safety production model. Artificial neural network has high similarity with chemical production safety evaluation system, and has outstanding advantages [52].

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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