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Safety Evaluation Model of Chemical Logistics Park Operation Based on Back Propagation Neural Network

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In order to study the chemical logistics park operation safety evaluation model based on BP neural network, this paper firstly introduces the learning algorithm of BP neural network and evaluation method of BP neural network. Then, from the viewpoint of chemical logistics park operation safety influence factors, we establish the chemical logistics park operation safety evaluation index system. In addition, a safety evaluation model of chemical logistics park based on neural network is constructed, and the network model is trained and simulated by using the neural network toolbox graphical user interface. Finally, it is proved that the error of the model reaches the predetermined range and has certain practicability. Thus, it is concluded that the safety evaluation model has quite good performance in application in chemical logistic park.

1. Introduction

The development of chemical industry park in China is rapid in recent years, and at present, there are many parks with more mature development. Whereas, affected by the central and western regions close to raw materials, low labor costs and other factors, the trend of chemical industrial park gradually developing from the eastern coastal areas to the central and western regions is obvious (Ren et al., 2014). With the development of the chemical industry and market division, it is taken into account that the chemical logistics operation is complex, equipment is specialized and safety requirements are higher and other characteristics, so international production type chemical enterprise itself rarely engaged in chemical logistics. Instead, the logistics business is outsourced to specialized third party logistics service provider, which makes the chemical logistics rapidly develop. And then chemical logistics park provides supporting logistics service for the chemical industry, such as warehousing, transportation, packaging business of chemical raw materials and products (Zhang et al., 2015).

As China's chemical industry park presents the scaled and intensive development trend, with the emergence of a series of chemical industrial clusters, although many regions have introduced chemical logistics park construction planning, few studies were carried out on the operation mode and operation safety evaluation of chemical logistics park, thus lacking perfect theoretical as the guidance. To realize the efficient and safe operation of chemical logistics park (Sun et al., 2014) has become the key to fully realize the scale benefit of chemical industry cluster. In this paper, on the basis of existing research results, combined with the actual situation of chemical logistics park, the chemical logistics park operation safety evaluation model is constructed by using neural network, to make an evaluation and analysis of factors affecting the operation safety, so as to provide a reference for improving the park operation safety level.

Through analyzing the existing literature, the logistics operation mode and chemical logistics park layout mode firstly in this paper, the chemical logistics park operation mode and chemical logistics park operation safety evaluation index system are put forward (Wang et al., 2017). Then, by constructing a neural network evaluation model, the chemical logistics park operation safety is evaluated. Finally, an example is given to illustrate the effectiveness and operability of the proposed model.

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2. Method

BP network is back propagation network. And BP neural network is a widely used neural network model at present. The essence is to adjust the weights of each layer so that it can learn and memorize the learning sample set. The training process consists of two parts: forward process calculation node error and reverse process adjustment weight. BP network is generally composed of 3 neuron layers, namely input layer, hidden layer and output layer. All the processing units of each layer form full interconnection connection (Zhong et al., 2016), and there is no connection between the processing units in the same layer. The transfer function of each layer is sigmoid type function.

2.1 BP neural network evaluation method

BP network is a one-way propagation multilayer feedforward neural network, which is similar to multilayer perceptron in structure. The BP network was proposed by scientists in 1986. BP networks are widely used in the field of science and technology (Yune et al., 2016). on the basis of fully considering the difficulty understanding degree of the current artificial neural network algorithm, the BP network is selected as the evaluation model. It has the advantages of simple structure, adjustable parameters, various training algorithms, good maneuverability and so on advantages, and it can achieve a good risk assessment for high speed railway. The BP network model is shown in Figure 1. BP network has three or more than three layers neurons, including input layer, hidden layer and output layer (Lele et al., 2016). The hidden layer can be a single layer or a multilayer. The neurons between the adjacent layers are fully connected, and there is no connection between the neurons in each layer.

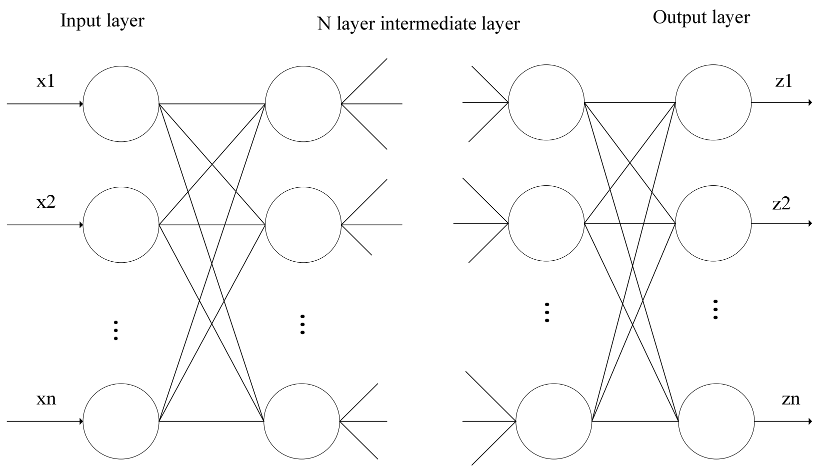

Figure 1: Neural network model

The basic principle of BP network is that after a set of input vectors are supplied to the network, the neurons are stimulated, and the activation values propagate through the intermediate layer to the output layer. The output layer nodes respond to the stimulus to get the corresponding output, and complete a forward propagation (Xing, 2016). Then, the error of the actual output and expected output of the system is analyzed, and through the output layer, is passed through each intermediate layer according to the error reduction direction, and the weights and thresholds are adjusted until the input layer, so as to complete the back propagation, that is, BP algorithm (Ramli et al., 2014). With the adjustment of weights and thresholds, the error between the actual output and the expected output is reduced until the error reaches a predetermined range, and then the learning is stopped. The whole process realizes a mapping relationship between input data and output data.

2.2 Learning algorithm of BP neural network

The principle of BP neural network model involves many mathematical formulas, parameters and operation rules (Zhang et al., 2014). In order to facilitate the understanding of basic logic thinking of the neural network model in the process of analyzing and evaluating the research object, it needs to briefly understand the algorithm flow of BP neural network model. The BP algorithm is based on gradient descent. By adjusting weights and thresholds, the mean square error between the output expectation value and the actual output value of the neural network tends to be the minimum. The schematic diagram of the BP algorithm is shown in Figure 2.

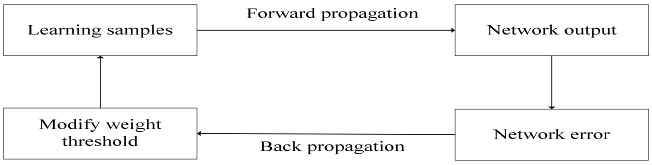

Figure 2: Schematic diagram of algorithm

This section takes the three-layer BP network as an example to introduce the learning process of BP network. The input node is x_i, the hidden layer node is y_j, and the output node is z_l. The connection weight between input node and hidden layer node is w_{ij}, and the connection weight between hidden layer node and output node is v_{lj}. The threshold of each neuron in the hidden layer is θj, and the threshold of each neuron in the output layer is θl. The excitation functions of the hidden layer and the output layer are f. The expected output of the output node is t_l. The calculation formula of BP network model is as follows:
The output of hidden layer nodes:

$$\mathrm{y}_j = f(\sum w_{ji} x_i \quad \theta_j) = f(net_j) \tag{1}$$

The output of output layer nodes:

$$z_l = f(\sum v_{lj} y_j \quad \theta_l) = f(net_l) \tag{2}$$

Mean square error function between actual output and expected output:

$$\mathrm{E} = \frac{1}{2}\sum_l (t_l \quad z_l)^2 = \frac{1}{2}\sum_l (t_{jl} \quad f(\sum_j v_{lj} f(\sum_i w_{ji} x_l \quad \theta))^2 \tag{3}$$

Weight modification between input layer and hidden layer node:

$$w_{ji}(k+1) = w_{ji}(k) + \Delta w_{ji} = w_{ji}(k) + \eta' \delta_j x_i \tag{4}$$

From the above formulas, it is known that, the error representing the output node in the hidden layer node error is back transmitted to the error of the hidden layer node through the weight.
In order to describe the implementation process of the algorithm, the flow chart is used to represent the algorithm, as shown in Figure 3.

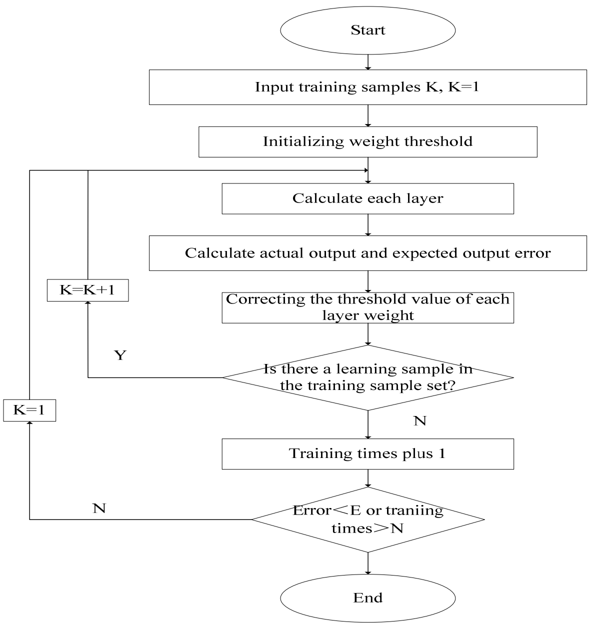

Figure 3: Flow chart of algorithm

3. Construction of operation safety evaluation model for chemical logistics park

3.1 Application of BP neural network model

Chemical logistics park is a new park form (Shao et al., 2013). The current domestic scholars made little research on it (Thompson et al., 2013). The evaluation involving the operation safety aspects has no historical data for being used, so the expert scoring is used to obtain the sample data of chemical logistics park operation safety evaluation index system. In order to prevent part of the neurons reaching the saturation, the sample data should as far as possible in the interval. As a result, the operation safety evaluation grade is divided into excellent, good, moderate, and poor. The better the operation safety is, the higher the corresponding numerical score is. In this paper, through the expert scoring form for expert survey to score, we obtained the group sample data, as shown in table 1.

Table 1: Chemical logistics park operation safety evaluation sample data

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
U11	0.82	0.79	0.81	0.87	0.85	0.84	0.8	0.9	0.83	0.86	0.92	0.89	0.88	0.91
U12	0.82	0.79	0.81	0.87	0.85	0.84	0.8	0.9	0.83	0.86	0.92	0.89	0.88	0.91
U21	0.79	0.76	0.79	0.86	0.82	0.82	0.86	0.89	0.86	0.79	0.87	0.79	0.85	0.87
U22	0.8	0.77	0.8	0.86	0.83	0.83	0.81	0.89	0.86	0.84	0.88	0.8	0.83	0.79
U23	0.72	0.69	0.76	0.84	0.75	0.79	0.77	0.87	0.84	0.83	0.89	0.72	0.78	0.75
U33	0.76	0.73	0.78	0.85	0.79	0.82	0.8	0.88	0.85	0.84	0.88	0.76	0.8	0.83
U32	0.78	0.75	0.79	0.86	0.81	0.81	0.83	0.89	0.86	0.84	0.87	0.78	0.86	0.85
U41	0.9	0.87	0.85	0.9	0.93	0.88	0.86	0.93	0.9	0.86	0.84	0.9	0.89	0.89
U42	0.88	0.85	0.84	0.89	0.91	0.87	0.81	0.92	0.89	0.86	0.84	0.9	0.89	0.87
U43	0.85	0.82	0.83	0.88	0.88	0.85	0.88	0.91	0.88	0.83	0.9	0.81	0.84	0.79

According to the weight value of each index, the 14 groups of sample data were weighted and calculated, and the results were shown in table 2.

Table 2: Chemical Logistics Park operation safety evaluation score table

Sample	1	2	3	4	5	6	7
Score	0.8237	0.7937	0.8123	0.8718	0.8537	0.8405	0.8294
Sample	8	9	10	11	12	13	14
Score	0.8767	0.861	0.8526	0.8762	0.8325	0.8402	0.85

Through the previous analysis, the number of neurons in the input layer is determined, and the number of neurons in the output layer is known. The number of neurons in the hidden layer is determined according to the formula. On this basis, the neurons in the hidden layer are continuously increased and reduced. The number of neurons in the hidden layer is determined by the selection, and the satisfactory selection is taken. Therefore, the network structure of safety assessment model of chemical logistics park based on neural network is shown in Figure 4.

The first groups of sample data in all the sample data are taken as training samples, and each index in the evaluation index system of sample is taken as input data. The weighted mean of each sample data is desired as output data, and a BP neural network is created for training by MATLAB neural network toolbox CUI. In order to make the sample data get better training, we use the dynamic gradient descent algorithm with adaptive learning rate, momentum back propagation and dynamic adaptive learning rate, BP algorithm of Levenberg_Marquardt three training function, and for each training function, we adopt the tansig and lodsig two kinds of transfer functions for the comparative analysis.

The training results of parameter setting network are analyzed and compared, and the conclusion are as follows:

On the whole, the convergence rate of trainlm training function is the fastest, and only the network with trainlm training function can achieve the high matching of training samples. For each layer transfer function, the lodsig function converges faster than the tansig function, and the simulation error is the minimum. Therefore, after comprehensive consideration, this paper uses tansig function and lodsig function, respectively, in training safety function and transfer function of each layer in the operation safety evaluation of chemical logistics park.

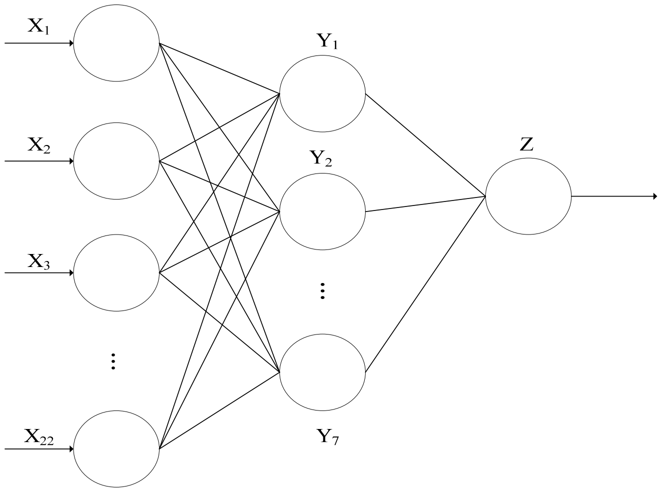

Figure 4: Network structure diagram of operation safety evaluation model of chemical logistics park based on Neural Network

3.2 Simulation of network model

In the sample data, the latter 6 sets of sample data n and the corresponding data m calculated by weight are used as input data and expected output data of model simulation. After completing the training of the sixth parameter setting network, click "Simulate" in "Network:BP", and simulate with the input data n in the trained network. The output variable of the simulation is sim_outputs, the simulation error is sim_errors, and the specific simulation results are compared with the expected results, as shown in table 3.

Table 3: Comparison table of neural network simulation output and expected output:

Serial number	Serial number	Actual output	Error
1	0.8762	0.86892	0.0072807
2	0.8325	0.84941	-0.016911
3	0.8402	0.8365	0.0036991
4	0.85	0.8475	0.0025045
5	0.87213	0.87352	-0.0013889
6	0.8447	0.85407	-0.0093741

The error variation curve is obtained, as shown in Figure 5.

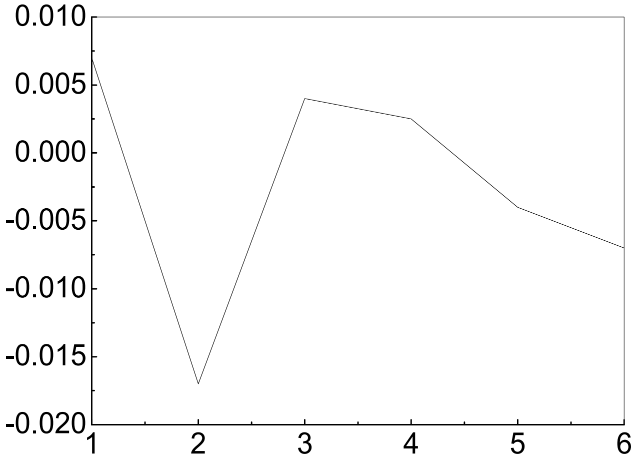

Figure 5: Curve of error variation

We found that by simulation results in Figure 5, the error of the actual output and the expected output is very small, which shows that the chemical logistics park operation safety evaluation model established by neural network is effective.

4. Conclusion

In this paper, the chemical logistics park operation safety evaluation is studied based on BP neural network model. First of all, from the characteristics of three kinds of chemical logistics park layout modes and its applicable conditions, combined with different characteristics of chemical logistics park and the specific needs of enterprise, we provide the basis for arrangement of proper planning of logistics park infrastructure facilities layout. According to the chemical logistics park operation safety evaluation index system, we construct the chemical logistics park operation safety evaluation model based on BP neural network, and divide the operational safety into excellent, good, moderate and poor four levels. Then, MATLAB neural network toolbox graphical user interface is applied in network training and simulation, so the error of the model reaches a predetermined range. However, due to the space problem, this paper lacks the actual case to compare the security of the typical operation mode.

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