

# The Application of the Maximum and Minimum Ant System Neural Network in the Calculation of Hydraulic Gradient for Paste Pipeline Transportation

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**Abstract.** Hydraulic gradient is an important parameter in the design of paste underground treatment system, which determines the energy consumption and operation cost. In order to grasp the accurate result of hydraulic gradient, we apply the MMAS-BP neural network to the calculation of hydraulic gradient, clarify the basic idea and establish the prediction model of hydraulic gradient. The practical application shows that the model has the fastest convergence and global nature of the maximum and minimum ant colony algorithm, and has strong mapping effect of BP neural network. The result fully meets the practical application needs, and provides an important method for paste filling mining system design.

## 1. Introduction

Green mining is imperative and backfill mining is an important part of green mining<sup>[1]</sup>. The fly ash paste can solve the problem of environmental pollution caused by fly ash and meet the needs of backfill mining, which is conducive to the sustainable development<sup>[2]</sup> of coal enterprises. The pipeline transportation is the key link of the filling system, and the hydraulic gradient is one of the most important parameters of the pipeline transportation. The result of precision plays an important role<sup>[3]</sup> in the practical application of the project. The influence factors of hydraulic gradient are complex<sup>[4]</sup>, which are closely related to many factors such as physical and chemical properties, paste characteristics and pipeline characteristics. The study of hydraulic gradient mainly goes through three processes. The first stage was B.M.Makaeabb, a former Soviet scholar, who first proposed the calculation based on diffusion theory<sup>[5]</sup>. The second stage is the calculation of gravity theory<sup>[6]</sup> based on M.A.Bennkahob, a former Soviet scholar in 1944. In the third stage, the former Soviet Union Coal Mine Research Institute put forward the calculation based on energy theory<sup>[7]</sup>, and the main formula was put forward by Anshan Mine Design Institute and Jinchuan mining industry<sup>[8]</sup>. However, the hydraulic gradient has the influence of nonlinear and multiple factors. The above research is mainly based on isolated factors and experience summaries. At present, there is not a set of unified guidance and general formula<sup>[9]</sup>, and the related aspects of sediment transport, oil and gas transmission and ore transport are studied<sup>[10]</sup>. There is less literature on the study of the hydraulic gradient of the fly ash gypsum pipe. Based on the above problems, this paper is based on the MMAS-BP neural network to predict the hydraulic gradient of coal fly ash paste filling, and set up a corresponding model. The prediction results are of high accuracy and fully meet the actual needs. It provides a new and important theoretical method for the design of paste filling system, which has important practical significance.



## 2. The basic idea of the MMAS-BP neural network

### 2.1. BP neural network

Neural networks mainly include biological and artificial neural networks. BP neural network is one of the most applied artificial neural networks. It is a multilayer feedforward neural network. The topology structure is input layer, hidden layer and output layer. The training mode adopts the error reverse propagation algorithm, and the network structure is shown in Figure 1. There are two main features of the BP neural network<sup>[11]</sup>. One is the connection of neurons between layers. The two is that the training process is divided into two processes: positive and negative. The forward training process refers to the forward propagation of the signal. The sample is input from the input layer and is processed by the hidden layer to the output layer. For example, the value of the output layer is different from the expected value, then the reverse training is done. Reverse training refers to the backpropagation of errors. By returning the error along the original route, it is apportioned to each layer of neurons, and the weights of each unit are modified to make the error smaller. The two training processes are repeated repeatedly until the error is within the permitted scope, and the learning and training of the network is suspended. Practice shows that BP neural network has strong nonlinear mapping ability.

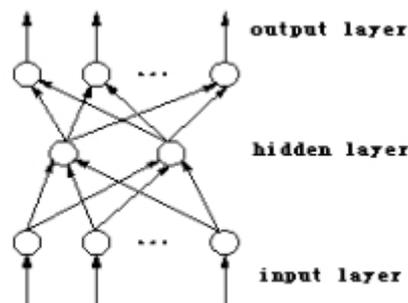


Figure 1. A structure diagram of a three layer BP neural network

### 2.2. Maximum and minimum ant system(MMAS)

Ant colony algorithm<sup>[12]</sup> is an optimized probabilistic algorithm for finding the best path. It was first proposed by Marco Dorigo, a Italy scholar. The idea is based on the way ants search for food. Ant groups choose a walking path to food by random way. All paths are released on all paths. The accumulation of pheromones in the shortest path will be more and more, and the number of ants attracts more. Under the mechanism of positive feedback, the ant group is concentrated on the best path. The algorithm has the advantages of real-time search process, fast search process, distributed computing efficiency and global search. It is mainly used in optimizing combination to find the optimal solution. The maximum and minimum ant system, called MMAS, is an improvement of the ant colony algorithm. It can not only optimize the weights and thresholds of the BP neural network, but also optimize the structure of the BP neural network, and have better performance.

### 2.3. Training of BP neural network based on MMAS

In order to overcome the shortcomings of BP neural network, such as slow training speed and easy to fall into local minimum<sup>[13]</sup>, MMAS is introduced into BP neural network. The weights, thresholds and structures of BP neural network are trained by MMAS, and the advantages of MMAS are used to make up for the deficiency of BP neural network. The training process of the BP neural network based on MMAS is as follows<sup>[14]</sup>:

The first step is initialization. The basic parameters include the maximum pheromone  $a_{max}$ , the minimal pheromone  $a_{min}$ , the random number of individual  $M$ , the number of hidden layer  $W$ , the maximum  $W_i$  of each hidden layer, the maximum cycle number  $D_{max}$ , and the ant number  $s$ .

The second step, ants start from the first node in parallel, and process them one by one until the last node. For the case of  $n$  only ants, the specific operation is to analyze the nodes first, to judge the basic

situation of the nodes, and then to calculate the probability according to the selection rules of the elements, and to select an element in the set of weights and thresholds corresponding to the previous node according to the rotation of the wheel. The element selection rule is carried out according to the following formula (1).

$$P_j^n(O_b) = a_j(O_b) / \sum_{l=1}^M a_l(O_b) \quad (1)$$

Formula:  $O_b$  —the set of weights and thresholds;  $j$  —elements;  $a_i(O_b)$  —the pheromone  $O_b$  in the set  $a_i$ .

In the third step, in each iteration, the neural network corresponding to the whole ant colony solution is established, the sample is input, the mean square error  $MSE$  of the neural network is calculated, the mean square error  $MSE_{best1}$  of the optimal path for the ant is recorded, the training is trained with the BP neural network, and then the mean square error  $MSE_{train}$  after the training is recorded. It is specifically expressed as the following formula (2).

$$MSE_{best} = \min\{MSE_{best1}, MSE_{train}\} \quad (2)$$

The fourth step is to update the elements and pheromones. For each node, the update is done according to formula (3) and formula (4).

$$a = \begin{cases} (1 - \rho)a + \Delta a & \text{when finding the best path} \\ (1 - \rho)a & \text{other circumstances} \end{cases} \quad (3)$$

Formula:  $\rho$  —pheromone volatilization factor.

$$\Delta a = 1 / MSE_{best} \quad (4)$$

The fifth step is to repeat second to fourth steps until the  $D_c$  is not less than  $D_{cmax}$ .

The sixth step is to find the optimal path solution by MMAS, establish BP neural network, carry out learning and training, and fine tune the weights, thresholds and structures of the neural network.

### 3. The establishment of hydraulic slope prediction model

#### 3.1. Basic ideas

The transport of fly ash paste needs to overcome the resistance generated by the wall and the resistance between the internal flow layers, which is called hydraulic gradient. To study hydraulic gradient, we need to start with its influencing factors. In practice, the relationship between hydraulic gradient and three factors, such as concentration, velocity and diameter, is studied. Because the relationship between them is multiple input and single output, and the influencing factors change at all times, it presents a nonlinear fuzzy system. They cannot be established by mathematical equations. Thus, the strong nonlinear mapping ability and generalization function of BP neural network are utilized. The Kosmogorov theorem points out that if the hidden nodes can be set freely according to the needs, a three layer feedforward network can be used to approximate any complex continuous function with arbitrary accuracy. Therefore, a hydraulic gradient prediction model of three layers of fly ash paste transportation can be established. The first level is the input layer, and the three neurons are concentration, velocity and diameter. The second layer is a hidden layer. The third level is the output layer and a neuron for transporting hydraulic gradient.

Because of the shortcomings of the BP neural network, the prediction model of the hydraulic gradient for the transport of the fly ash paste is based on the modeling idea of the BP neural network based on the MMAS. First, the experimental data is blurred, and then as the input and output of BP neural network, and the MMAS neural network with high efficiency, distribution and global characteristics is used to learn and train with BP neural network, and the nonlinear mapping model between the parameters and the related indexes is obtained.

3.2. Algorithm implementation

The algorithm of establishing the hydraulic gradient prediction model for paste transportation of fly ash is as follows.

The first step is the determination of the objective function. The objective function is represented by the least square objective function, such as formula (5).

$$f(X) = \sum_{i=1}^r (U_i^s - U_i^q)^2 \tag{5}$$

Formula:  $r$ —the number of test groups;  $U_i^s$  —the actual output of group  $i$  test;  $U_i^q$  —the expected output for group  $i$  test.

The second step is the data obtained from pipeline transportation test as a sample set and normalization of the sample set data.

The third step is to study the BP neural network. At the same time, the weight, threshold and structure of the neural network are optimized by MMAS. The influence factors of the hydraulic gradient of pipeline transportation and the nonlinear mapping of hydraulic gradient are set up, and the hydraulic gradient prediction model of the fly ash paste transportation is obtained.

4. Practical application

In order to establish the accurate prediction model of the hydraulic gradient of the fly ash paste slurry, based on the data of the loop test<sup>[15]</sup>, eleven sets of data are taken as samples, of which the first to ninth test is the training sample, and the test sample of No. tenth and No. eleventh is the test. Due to the large difference of numerical units and sizes, the normalization of samples is needed.

In the MATLAB environment, the prediction results of the model are shown in Table 1, and the effect of the prediction is shown in Figure 2.

Table 1. Sample data and prediction results

Sample number	Concentration on X <sub>1</sub> (%)	Current speed X <sub>2</sub> (m/s)	Pipe diameter X <sub>3</sub> (mm)	Hydraulic gradient Y <sub>1</sub> (kPa/m)			
				Measured value	Predicted value	Absolute error	Relative error(%)
1	1(51)	1(1)	1(75)	3.6	3.582	-0.018	-0.5
2	2(53)	1(1)	2(100)	3.7	3.636	-0.064	-1.7
3	3(55)	1(1)	3(125)	3.5	3.543	0.043	1.2
4	2(53)	2(1.5)	1(75)	5.0	5.035	0.035	0.7
5	3(55)	2(1.5)	2(100)	6.5	6.480	-0.020	-0.3
6	1(51)	2(1.5)	3(125)	3.7	3.724	0.024	0.6
7	3(55)	3(2)	1(75)	8.3	8.258	-0.042	-0.5
8	1(51)	3(2)	2(100)	7.5	7.476	-0.024	-0.3
9	2(53)	3(2)	3(125)	5.6	5.612	0.012	0.2
Test sample							
10	51	1.5	100	6.2	6.194	-0.006	-0.1
11	53	2	100	8.1	8.055	-0.045	-0.6

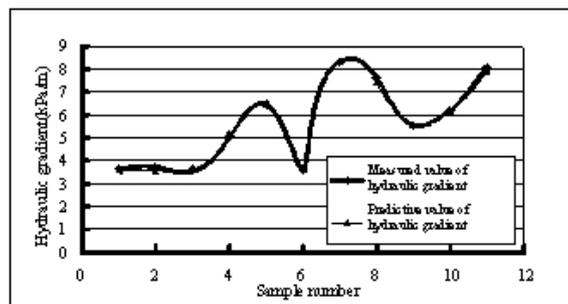


Figure 2. MMAS-BP neural network model for predicting the effect of hydraulic gradient

From table 1 and Figure 2, we can get the relative error of predicted values: the absolute error of the hydraulic gradient of the fly ash paste is -0.064 kPa/m, the smallest is -0.006 kPa/m, and the relative error is -1.7% and the minimum is -0.1%. The error between the network model and the measured values is within the allowable error range. It is proved that the prediction accuracy of the model is high, which fully meets the requirements of actual production. At the same time, the model is also easy to operate, strong adaptability and reliability in practical application.

## 5. Conclusions

First, the analysis of pipeline hydraulic slope is based on MMAS-BP neural network. It can predict the main factor concentration, flow rate, pipe diameter and hydraulic gradient of the hydraulic gradient of the fly ash paste, so as to predict the hydraulic gradient of the paste by input of different concentration, flow rate and pipe diameter. The simulation shows that the absolute error of the model is -0.064 kPa/m, the minimum -0.006 kPa/m, the maximum relative error -1.7%, and the minimum -0.1%. The accuracy of the prediction is quite high in the range of allowable error of the test, which meets the practical application requirements.

Second, the application of MMAS and BP neural network in hydraulic gradient calculation can better predict the hydraulic gradient of the fly ash paste. The method is reliable and efficient, fully meet the actual requirements. It provides an important basis for the pipeline system design to reduce the energy loss in the filling pipeline.

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