Slope Stability Analysis Based on the Radial Basis Function Neural Network of the Cerebral Cortex

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ABSTRACT

The artificial neural network technology simulates the neural network structure of the cerebral cortex by establishing artificial neurons and sensors to solve nonlinear engineering problems, and establishes the prediction model for solving such problems. Rock slope stability is a hot research topic in the field of geotechnical engineering, especially for those slopes affected by the cyclic changes of water level. This paper establishes a slope stability prediction model based on the radial basis function neural network (RBFNN) of the cerebral cortex and introduces the genetic algorithm to eliminate the drawbacks of the cerebral cortex RBFNN, that is, slow convergence and local optimisation. The cerebral cortex RBFNN prediction model can predict the slope safety factor, with the relative error controlled between -5.16% and 6.02%. According to the cerebral cortex RBFNN prediction results, as the water level in the tailing pond changes cyclically, the rock mechanics parameters of the slope gradually weaken, which leads to the continuous decrease of the slope safety factor. The results can provide reference for the extension and application of the cerebral cortex RBFNN in the engineering field, and serve as guidance for the specific project safety maintenance.

Key Words: RBFNN, Genetic Algorithm, Slope Stability, Safety Factor, Water Level Changes

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Introduction

The artificial neural network has a strong nonlinear mapping capability as well as high fault tolerance and robustness. It is highly adaptable to nonlinear engineering problems, especially for random data processing and multi-sample data prediction. The artificial neural network simulates the complex neural network organization in the human brain and achieves neuronal connections and establishes a multi-layer perceptron to complete deep machine learning through specific algorithms (Jana *et al*., 2017; Lin *et al*., 2018; Kang *et al*., 2018; Kadri and Mouss, 2017; Wang *et al*., 2016; Hu *et al*., 2016; Sun *et al*., 2016). At present, artificial neural network has been widely used in engineering. The artificial neural network was optimised through the genetic algorithm that uses the meandered microstrip line to optimise the distribution of the total electromagnetic radiation power. The crack monitoring was targeted, and used the convolutional neural network and Naive Bayesian network to carry out data fusion to achieve the neural-network-based deep learning; The RBFNN-genetic algorithm was employed to quantitatively analyse the pits on the surface of

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the automobile engine cylinder (Piersanti *et al*., 2017; Chen *et al*., 2018; Yang *et al*., 2017). The regression neural network was improved by using the particle swarm optimization algorithm and predicted the rock burst in mine construction; A fourth-order matrix method was proposed for engineering reliability analysis based on artificial neural network; aiming at the safety of rock engineering under complex conditions, An applying artificial neural network was proposed and system science to realise the intelligent evaluation and spatio-temporal prediction of rock engineering. The earth-rock dam displacement inversion was achieved based on neural network. The foundation pit deformations were predicted and analysed through the genetic algorithm-BP neural network method. (Jia *et al*., 2013; Zuo *et al*., 2013; Feng *et al*., 2008; Zhang *et al*., 2005; Li *et al*., 2015). In summary, the artificial neural network technology has been widely used in many engineering fields, including electrical, mechanical, foundation pit, mining, geotechnical engineering and so on (Tang *et al*., 2017; Jung *et al*., 2017; Kim *et al*., 2017).

Based on the radial basis function (RBF) artificial neural network theory, this paper introduces the genetic algorithm to optimise the threshold of RBFNN, and utilises the slope safety factors of multiple samples to achieve the deep learning of RBFNN and establishes the genetic algorithm- neural network prediction model. Taking a specific project as an example, it predicts the slope stability of an open pit, which illustrates how the artificial intelligence technology is extended and applied in the engineering field.

Neural network

By simulating the functions of the biological brain for information receiving and processing, the neural network algorithm constructs the artificial neuron structure, receives external information through the perceptron, and allows the nerve centre consisting of numerous neurons to analyse the information on the research object and recognise the analysed object. In geotechnical engineering, slope stability is currently a hot research topic. It is closely related to the basic mechanical properties of rock-soil mass, especially the cohesion and internal friction angle. Therefore, this paper uses the deep learning function of the neural network algorithm to learn the known sample data to establish the neural network structure, and then determines the slope stability according to the relevant parameters of the research object. In this way, the neural network algorithm technology is extended and applied in the engineering field. This paper mainly uses the RBFNN theory. Generally speaking, RBFNN mainly consists of three layers of network topologies, including input layers, hidden layers and an output layer. This is a feed-forward neural network (Pirdashti *et al*., 2015; Heshmati *et al*., 2015; Do N A D *et al*., 2016). The neuron structure is shown in Figure 1:

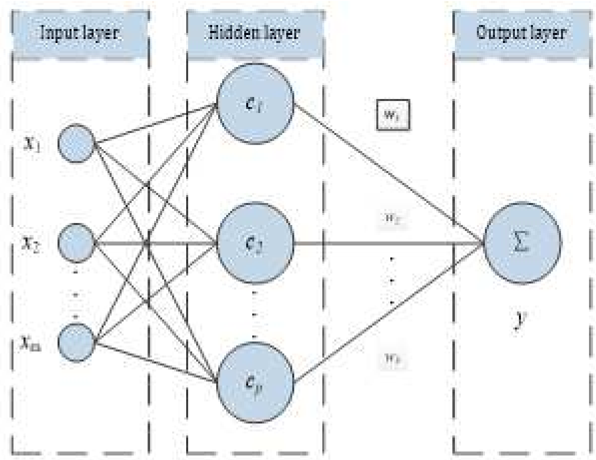

Figure 1. RBFNN neuron structure

The input layer of RBFNN is composed of input signal source nodes. Its main function is to transmit data information. The main function of the hidden layer is to spatially map the input data information. The number of hidden layers is subject to the specific engineering needs. The neuron kernel functions mainly include Gaussian function and Reflected Sigmoidal function. The radial basis function of RBFNN is defined in equation (1). In this paper, the Gaussian function is used as the radial basis function for the prediction model. The expression of the Gaussian function is shown in equation (2):

$$y(x_i) = \sum_{j=1}^{M} w_j \Phi\left(\left\|x_i - c_j\right\|\right) \tag{1}$$

$$\varphi(x_i) = \exp\left(-\frac{\left(\left\|x_i - c_j\right\|\right)^2}{2\sigma_i^{\ 2}}\right) \tag{2}$$

Where: x_i is the input layer signal source node; w_i is the connection weight between the hidden layer and the output layer; c_p is the centre of the j-th node; σ_i is the width factor, which is usually a constant; and $y(x_i)$ is the output of the i-th neuron at the j-th hidden node. As $\|x_i - c_j\|$ represents the modulus of the difference vector, and the distance is radially isotropic, $\Phi(\|x_i - c_j\|)$ is called the radial basis function.

Genetic algorithm

Based on Darwin's theory of evolution, through the genetic mechanism of "survival of the fittest", the genetic algorithm simulates the biological evolution process to find the optimal solution to the actual problem. The algorithm mainly involves such concepts as chromosome, gene, gene location and fitness. It selects the appropriate fitness function to evaluate the advantages and disadvantages of the parametric solutions, generates the solutions of the next generation by copying, crossing over and mutating different parametric solutions, and gradually eliminates the solutions with low fitness values, and retains those with high fitness values. This is similar to the biological evolution process, where the individuals that can adapt to the changes in the environment survive and those who do not are eliminated. Through continuous iterations, the genetic algorithm obtains the solution with the highest fitness function value, which is the optimal solution to the problem (Li, 2017; Mohanty *et al.*, 2016; Dhabal *et al.*, 2017; İnkaya *et al.*, 2015; Keshtkar, 2017; Wang and Xie, 2016; Huang *et al.*, 2016; Yuan *et al.*, 2017). The main implementation process of the genetic algorithm is shown in Fig.2:

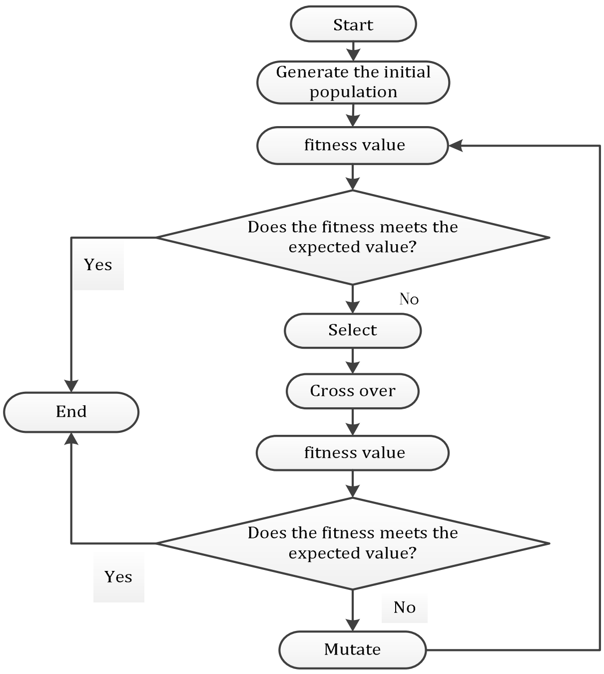

Figure 2. Implementation flow of the genetic algorithm

Genetic algorithm- neural network prediction model

Prediction process

This paper attempts to have the genetic algorithm and RBFNN improve each other to achieve the deep learning of the slope stability sample data so as to establish the genetic algorithm-neural network prediction model. First, it obtains the initial weight of RBFNN and the optimal solution to the threshold, and then achieves the learning of multi-sample data through RBFNN and predicts the slope stability in an actual engineering project. The detailed steps are as follows:

1) Determine the research object

Algorithm to find the optimal solution to the initial weight threshold of RBFNN, so the research object is the initial weight threshold of neural network.

2) Initialise the population and study individual coding

Use the real number encoding method. The encoding length is $l=n\times m+m\times t+m+t$, where, m, n and l are the numbers of input layers, hidden layers and output layers, respectively;

3) Calculate and set the fitness value

The fitness function is defined as the reciprocal of the sum of squares of the difference between the predicted output value and the expected value of the neural network, as shown in equation (3). According to this definition, the greater the fitness is, the smaller the prediction error of neural network will be and the better its adaptability will become:

$$J = \frac{1}{\sum_{i=1}^{n}\left(F(x_i) - F^*(x_i)\right)^2} \tag{3}$$

4) Perform selection, crossover and mutation according to the different fitness values of the individuals to obtain a new population

5) Repeat the above steps until the required settings are met or the maximum number of iterations is reached.

Model learning

Five main influencing factors, i.e., cohesion, internal friction angle, slope angle, unit weight of rock and pore pressure ratio, are selected as the input layers of the neural network model, and the safety factor as the output layer. From relevant data of the literatures, 100 groups of data are randomly selected as the learning samples for the neural network, as shown in Table 1:

By learning the samples, the model trains the RBFNN and establishes nonlinear relationships between input neurons and output neurons. 5 groups of slope stability data are selected as the test samples, with the results shown in Table 2.

From Table 2 and Fig.3, it can be seen that the relative error between the neural network predicted value and the actual value is small, indicating that the prediction accuracy meets the engineering requirements. Therefore, the effectiveness of the proposed neural network prediction model is verified.

Project instance

Project background

Sanshan Island Gold Mine Tailings Pond is located in Sanshan Island, Laizhou, Shandong. It was originally an abandoned open-pit gold mine, as shown in Fig.4. Since 2013, it has been used as a tailings pond for a concentrating mill. (Chen *et al.*, 2015, 2017; Qin *et al.*, 2017)The discharge of tailing water leads to the fluctuations in the water level of the tailings pond. From December 2015 to March 2017, water level measurement was carried out 24 times using the real-time continuous monitoring method. The water level changes are shown in Fig.5 below.

As can be seen from the figure, the water level from December 2015 to July 2016 and from October 2016 to March 2017 generally showed a downward trend, and the rate of water level change remained basically stable at about 2.5cm/d. However, the water level decreased significantly from July to August 2016, with the maximum rate of change being up to -29.3cm/d. During August - October 2016, the water level rose sharply, with the maximum rate of change being up to 15.6cm/d.

Table 1. Slope stability learning samples*

No.	Cohesion/KPa	Internal friction angle/°	Slope angle/°	Unit weight of rock/ $kN\cdot m^{-3}$	Pore pressure ratio	Safety factor
1	40.0	35.0	43.0	27.0	0.25	1.150
2	46.0	35.0	16.0	25.0	0.25	1.310
3	48.0	40.0	49.0	25.0	0.25	1.490
4	50.0	40.0	42.0	27.0	0.25	1.440
5	68.6	37.0	47.0	31.3	0.25	1.200
6	37.5	35.0	37.8	27.0	0.25	1.240
7	68.0	37.0	47.0	31.3	0.25	1.200
8	55.0	36.0	45.5	25.0	0.25	1.520
9	32.0	33.0	42.6	27.0	0.25	1.160
10	32.0	33.0	42.2	27.0	0.25	1.300
11	14.0	31.0	41.0	27.3	0.25	1.249
12	31.5	29.7	41.0	27.3	0.25	1.245
13	16.8	28.0	50.0	27.3	0.25	1.252
14	26.0	1.0	50.0	27.3	0.25	1.246
15	10.0	39.0	41.0	27.3	0.25	1.470
16	10.0	39.0	40.0	27.3	0.25	1.434
17	23.0	38.0	40.0	22.5	0.35	1.271
18	50.0	45.0	39.0	22.5	0.35	1.485
19	28.0	45.0	39.0	24.0	0.35	1.362
20	27.0	36.0	42.0	24.0	0.35	1.281

* Only part of the data are listed in Table 1 due to space limitation

Table 2. Samples for prediction and comparison of results

No.	Cohesion/ KPa	Internal friction angle/°	Slope angle/°	Unit weight of rock/ $kN\cdot m^{-3}$	Pore pressure ratio	Safety factor	Predicted value	Relative error/%
Y-1	10.0	36.0	45.0	22.0	0.25	1.020	0.965	5.39
Y-2	10.0	39.0	40.0	27.3	0.25	1.445	1.358	6.0208
Y-3	31.5	29.7	41	27.3	0.25	1.245	1.221	1.9277
Y-4	16.8	28	50	27.3	0.25	1.252	1.302	-3.99
Y-5	22.0	32.0	44.0	25.2	0.25	1.302	1.377	-5.76

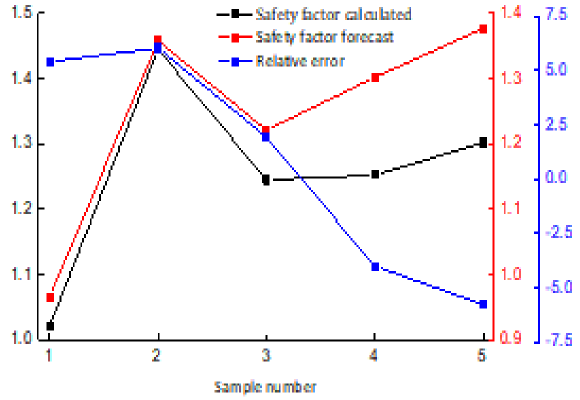

Figure 3. Comparison of slope safety factors

Figure 4. Tailings pond of the open mine pit

In order to analyse the impact of water level change on the slope stability, the mechanical properties of rock under different numbers of wetting-drying cycles are studied through laboratory mechanics test. The test data are shown in Table 3:

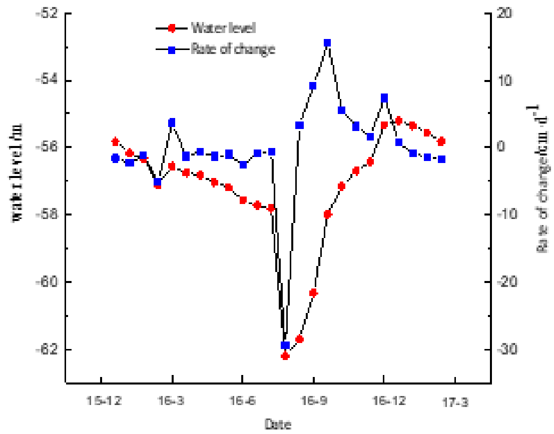

Figure 5. Water level variation chart of the tailings pond

Prediction of the slope safety factor of the tailings pond

With the help of the genetic algorithm-neural network slope stability prediction model, it can be seen from the rock mechanics parameters under different numbers of wetting-drying cycles that, with the number of cycles increasing, parameters like the shear strength of the slope gradually decrease, so does the predicted slope safety factor, as shown in Fig.6, which agrees with the actual situation of the slope in the tailings pond.

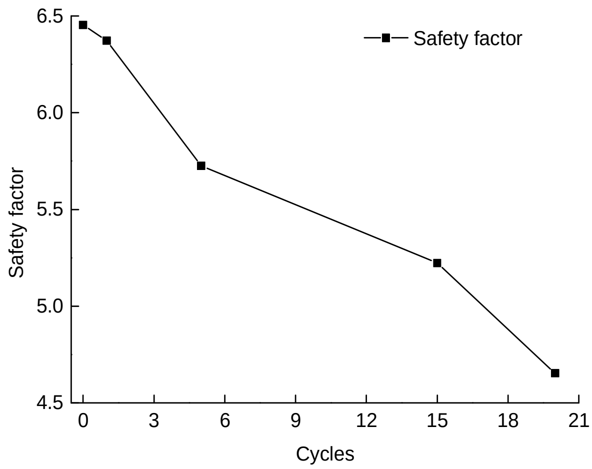

Figure 6. Slope safety factor of the tailings pond

Table 3. Rock mechanics parameters under different numbers of wetting-drying cycles

Number of cycles	Cohesion /GPa	Internal friction angle /°	Slope angle /°	Unit weight of rock / $kN \cdot m^{-3}$	Pore pressure ratio
0	3.91	50.01	40	22.8	0.25
1	3.63	47.89	40	22.8	0.25
5	2.96	45.02	42	20.6	0.25
15	1.97	42.01	42	19.5	0.25
20	1.19	41.34	42	19.2	0.25

Conclusions

By combining the genetic algorithm and RBFNN, this paper uses the global search ability of the genetic algorithm to solve the optimal initial weight threshold of RBFNN to prevent the neural network from easily falling into the local optimal solution. It also establishes the genetic algorithm-neural network slope stability prediction model, which achieves deep learning of multi-sample slope stability data, showing how the artificial neural network technology is applied in slope engineering.

Based on the established genetic algorithm-neural network slope stability prediction model, this paper takes the slope of the gold mine tailings in Sanshan Island as an example and analyses the slope stability under the influences of cyclic water level changes. Such changes lead to the decrease of the slope safety factor, bringing negative impacts to the slope stability of the tailings pond.

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