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Safety situation assessment of open pit slope based on improved d-s evidence theory

Song Jiang[2], Minjie Lian[2,3], CaiWu Lu[2,4]

Abstract. The safety Situation Assessment of open pit slope is a hot research topic in the field of information disaster science in recent years. In order to solve the problem of over-reliance on expert experience in the current assessment, a safety assessment method for open pit slope based on improved D-S evidence theory is proposed. This method integrates multi-source situation factors, gets the basic probability assignation, BPA, of DS evidence theory based on back propagation neural network, computes BPA by DS evidence theory in sequence, weakens the influence of human factors on BPA, improves the prediction accuracy of BPA and safety situation recognition rate of open pit slope. At last, the feasibility and effectiveness of this method in pit slope safety assessment are verified by the monitoring data of some open pit slope.

Key words. Open pit slope, d-s evidence theory, back propagation neural network, situation assessment.

1. Introduction

Pit slope is not an ideal continuum. Even a macroscopic intact rock pit slope contains a large number of microcracks of various sizes and shapes in its interior. Therefore, the pit slope system can be regarded as an open and complex system, whose stability are affected by many factors, including its own natural attributes factors and external mining factors. Its own natural attributes can be divided into ge-

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[2]Workshop 1 - School of Management, Xi'an University of Architecture and Technology, Shaanxi, 710055,PR China

[3]Workshop 2 - Sinosteel Mining Co.,Ltd, Beijing,100080, China

[4]Corresponding author: CaiWu Lu; e-mail: `lucaiwu@126.com(C.W.LU)`

ological factors and non-geological factors. In this complex system, with the change of the internal state, the pit slope is also constantly adjusting itself to reach a new equilibrium, otherwise landslide hazard will occur.

The macroscopic mechanical behavior of landslides is not determined by the occurrence and variation of one or several micro-cracks in the rock, but depends on its large number of different scales of microcracks that are distributed in disorder and are collective behaviors and statistical features. With the help of the mature Situation Assessment theory, the landslide development trend can be predicted and intelligent warning can be put forward. Situation Assessment is an important part of information fusion, but also one of the main content of Situation awareness. Situation awareness of pit slope disaster refers to the collection, processing and extraction of various factors affecting pit slope safety situation in the natural environment of open-pit mines, building an index system, and establish an evaluation model to evaluate the current slope safety posture index macroscopically and to predict the future Situation index.

From the perspective of pit slope safety, the purpose of the integration of the Situation Assessment of the open pit slope disaster and decision-making layer of early-warning system is to provide the decision-makers with a Situation Assessment of the safety of effective pre-control of pit slope disasters. In 1988, Endsley [1] gave a general concept of Situation awareness: "Situation awareness means knowing and understanding environmental factors within a certain space-time range and predicting the future development trend." In 1999, Tim Bass [2] at the first time put forward the concept of network Situation awareness and proposed that "network Situation awareness based on data fusion" will surely become the development direction of network management. Endsley and Bass laid the foundation for the research on network security Situation awareness. Later, researchers put forward more than a dozen of models of security Situation awareness and methods of Situation Assessment. Etzion [3] and Gal [4] of IBM Research Laboratory in Haifa ISRAEL Technion proposed using Bayesian network for Situation awareness. B dic [5] described the distributed complex Situation Assessment workflow in a loosely coupled system. Zhang S[6] proposed a network security situation analysis framework, which has a better assessment effectiveness in the intrusion network environment by detecting and analyzing intrusion and achieving Situation Assessment of network security. The above assessment methods not only provided a solution ideas for network security Situation Assessment, but also laid a good foundation for Situation Assessment research. But it also has some shortcoming. For example, the BPA in network security Situation Assessment based on D-S evidence theory is overly dependent on domain knowledge and expert experience, lack of objectivity assessment, and influence situation recognition rate.

In view of the above problems, this thesis proposes a situation assessment method based on improved D-S evidence theory. In this assessment method, firstly, the situation data is extracted from multiple data sources monitored by multi-sensor; secondly, learning is carried out by adopting the optimized BP neural network algorithm (GA-BP) based on a genetic algorithm (GA). The result is output as BPA of DS evidence theory. Finally, the D-S evidence theory is used to fuse BPA from different evidences in time domain. Then simulating through the microseismic alarm information, rainfall, displacement and other situation information. The results show that this method not only utilizes the DS evidence theory to deal with the uncertain information but also plays a role of self-learning and self-adaptability in BP neural network to solve the subjective problem of BPA. By combining the situation information, the method improves the Situation awareness of open pit slope rate.

2. Situation Assessment Based on Improved D-S Evidence Theory

2.1. Situation Assessment Based on D-S Evidence Theory

As a fusion method, D-S evidence theory can solve the unknown uncertainty of the problem. It uses the Dempster synthesis formula to fuse the trust functions of different evidences. As the evidence accumulates, the uncertainties are gradually reduced and accurate inference results are obtained. Then in accordance with the decision logic, the trust function after fusion is judged, and finally assessment realized[7]. In the D-S evidence theory, all the answers to a question are regarded as propositions and mutually incompatible, and the degree of trust assigned to each proposition is called BPA. Usually, BPA stands for the degree of trust in evidence. The larger the BPA, the greater the degree of evidence can be trusted. In the Situation Assessment based on D-S evidence theory, all kinds of situation types that may appear in the potential space are regarded as propositions, and the judgment of propositions by different safety equipment is taken as evidence. The situation BPA of evidence shows the trust degree of evidence to various situation states, D-S evidence theory incorporates different evidences of the situation BPA to solve the problem of uncertainty, in order to achieve pit slope safety Situation Assessment.

$$\tau = \tau_0 \left(1/2 - \xi\right) , \tag{1}$$

2.2. Situation Assessment Model Based on Improved D-S Evidence Theory

BPA assignment in pit slope safety Situation Assessment based on D-S evidence theory is a subjective judgment of man and a measure of confidence in evidence. The assignment of the BPA depends on expert experience and domain knowledge. In complicated mining environment, there are many monitoring devices, complicated structures and interaction of influencing factors. It is difficult to determine the influence degree of various factors on the pit slope safety situation based on expert experience alone. In order to solve the too subjective problem in the process of BPA assignment, a pit slope safety Situation Assessment method based on improved D-S evidence theory is proposed, which uses GA-BP to determine BPA, reduces the influence of subjective factors and improves the objectivity of Situation Assessment. This method divides the situation into three types: normal situation, abnormal situation and unknown situation. It is represented by the state space $\{NA\theta\}$, N represents the normal situation, A represents the abnormal situation and θ represents the unknown situation. The pit slope safety Situation Assessment model is shown in Figure 1.

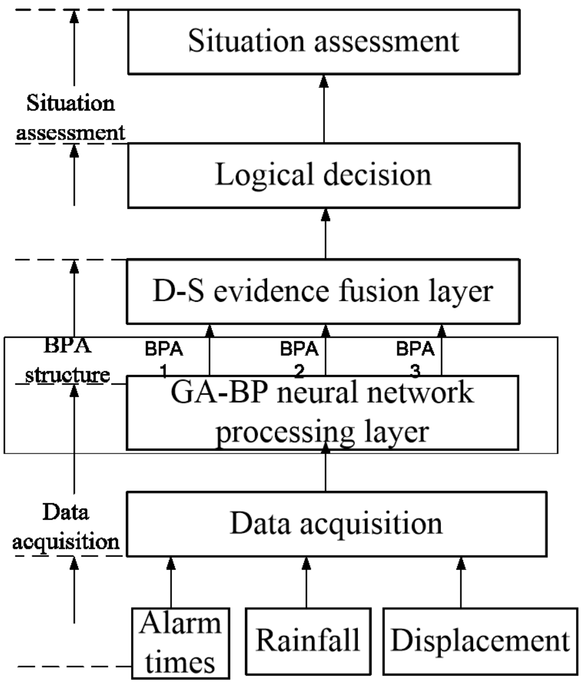

Fig. 1. The Situation Assessment model based on improved D-S evidence theory

The working steps of pit slope safety Situation Assessment based on improved D-S evidence theory is as follows.

Step 1 Data Acquisition. Collect the situation information provided by the monitoring equipment and extract the situation index and normalize it.

Step 2 BPA Construction. In the GA-BP neural network processing layer, optimized GA-BP algorithm based on genetic algorithm is used to train and learn the sample set formed by multidimensional situation index to determine the situation BPA.

Step 3 D-S Evidence Fusion and Situation Assessment. According to the situation BPA output by the BP neural network, the Dempster synthesis formula continuously merges the new evidence situation BPA and makes Situation Assessment based on the decision logic.

3. Situation Assessment Model of Improved D-S Theory

3.1. Data Collection

Referring to traditional risk assessment results of slop safety, data of multi-source situation information shall be collected by adopting the assessment strategy of "from one part to the whole, from the bottom up", and integrating the original data from such monitoring devices as microseismic monitoring unit, water gauge and GPS, mainly including microseism alert logs, rainfall amount and GPS displacement data. Generally, the slope stability is related to its internal structure, and the vulnerability depends on the amount of microscopic checks inside of the slope system. Macroscopic rules of the slope system disruption and evolution can be found from multi-angle and multi-level situation information. Reduce uncertainty in the situation assessment of open pit slope safety by collecting and analyzing alert logs, rainfall amount and displacement at threat level, and integrating situation information from various aspects, and then assess overall security status of the system[8].

According to the index system requirements for situation assessment of slope safety, collect situation indexes indicating macroscopic slope from the original data to be input parameters of the back propagation neural network. The input parameters, detailed situation indexes and corresponding descriptions are shown in Table 1.

Table 1. Input parameters and situation indexes of back propagation neural network

Input parameter	Situation index name	Describe
X1	Microseismic alert log	Alert log times
X2	Rainfall in the region	Rainfall
X3	GPS displacement data	Displacement

The situation indexes are collected mainly by the following method from the original data, and number of the indexes is mainly used to calculate occurrence frequency of situation indexes per unit time.

$$E = E_0\left(1 - \gamma\tau\right) , \tag{2}$$

Therein: D_k represents the indexes of one situation, and N_{sk} is the total number of situation indexes in unit time.

Unitize the various original data formats to make the data value in range from 0 to 1. The unitization formula is as followed:

$$E = E_0\left(1 - \alpha\left(1/2 - \xi\right)\right) , \tag{3}$$

Therein: X means the value of original situation index, X_{min} means the minimum value of situation index, X_{max} means the maximum value of situation index, and X' means the unitized value of situation index.

3.2. BPA Construction

In order to solve the over-subjectivity problem of D-S evidence theory during BPA construction, the back propagation neural network is used to acquire BPA value, based on which genetic algorithm (GA) is used to optimize structure parameters of the back propagation neural network to solve the problems such as slow convergence speed and local minimum, so that the BPA prediction accuracy can be improved. Featured in self-adaptation, self-learning and objectivity, the back propagation neural network is divided into input layer, hidden layer and output layer, and its processing includes training and execution, which means to train before test[9]. Input-output formula of back propagation neural network is shown as formula (4):

$$h(\xi) = h_0 \left[1 - (1-\beta_1)(\xi + 1/2)\right] \cdot \left[1 - (1-\beta_2)(\eta + 1/2)\right] , \tag{4}$$

Therein: W means the connecting weight values of each layer, I means the input of back propagation neural network, θ means threshold, f means transfer function, and y means the output of back propagation neural network.

In BPA construction, optimize connecting weight values and thresholds of the back propagation neural network by adopting GA, so that its convergence speed and accuracy can be improved. Through a series of operations including encoding, producing a group, computing adaptability, replication, intersection and variation, GA seeks the optimum solution from multiple zones in global solution space. The optimized back propagation neural network based on GA can solve problems such as slow convergence of neural network and local optimization, so that the BPA prediction accuracy can also be improved. In practical application, the back propagation neural network generally uses empirical formula to determine the number of nodes in hidden layer[10], which is shown in formula (5).

$$\rho = \rho_0 \left[1 - (1-\beta)(\xi + 1/2)^2\right] , \tag{5}$$

Therein: j means the number of nodes in hidden layer, i means the number of nodes in input layer, k means the number of nodes in output layer, α is an integer and within the scope from 0 to 10. In the case of k=3, i=4, α=7, j, the number of nodes in hidden layer of back propagation neural network is 9.

In BPA construction, situation indexes are taken as input parameters of input layer in the back propagation neural network, and output of the output layer is taken as situation BPA needed by the D-S evidence theory. With many variables, determination of situation BPA is dynamic, where human factor plays a major role. Due to many uncertainties, complicated logical relations and difficulty in dynamic changes, it is difficult to establish situation BPA model[11]. According to objective statistical data and knowledge and experience that the more alert logs, the more rainfall amount, the more obvious displacement, and the more probable the landslide situation. Therefore, establish situation indexes, training samples of slope safety situation status BPA and construction principles of situation BPA on the basis of a large number of documentary materials. Construction principles of situation

BPA are shown in Table 2 and Table 3. Relations between situation indexes and situation grades are shown in Table 2. In Table 2, N_h, N_m and N_l are respectively high, medium and low grades of normal situation N, A_h, A_m and A_l are respectively high, medium and low grades of abnormal situation A, and θ is unknown situation.

Table 2. Matrix table for situation indexes and situation grades

NO.	X1	X2	X3	Situation grades		
1	[0,300)	[0,2400)	[0,0.4)	N_h	A_1	θ
2	[0,300	[2800,0)	[0,0.4)	N_m	A_1	θ
3	[0,300)	[0,2400)	[0.4,1)	N_m	A_m	θ
4	[0,300)	[0,2400)	[1,0)	N_m	A_m	θ
5	[0,300)	[2400,2800)	[0.4,1)	N_m	A_m	θ
6	[300,450)	[2400,2800)	[0.4,1)	N_m	A_m	θ
7	[300,450)	[0,2400)	[0,0.4)	N_m	A_m	θ
8	[450,0)	[0,2400)	[0,0.4)	N_m	A_1	θ
9	[450,0)	[2400,2800)	[0.4,1)	N_m	A_m	θ
:	:	:	:			
51	[450,0)	[2800,0)	[0.4,1)	N_1	A_m	θ
52	[450,0)	[2800,0)	[0,0.4)	N_1	A_m	θ
53	[300,450)	[2400,2800)	[0,0.4)	N_m	A_m	θ
54	[450,0)	[2400,2800)	[0.4,1)	N_m	A_m	θ
55	[450,0)	[2800,0)	[1,0)	N_1	A_h	θ

Relations between situation grades and situation BPA are as shown in Table 3.

Table 3. Relations between situation grades and situation BPA

Situation grade	Situation BPA
N_h	0.7˜1.0
N_m	0.4˜0.7
N_l	0˜0.4
A_h	0.7˜1.0
A_m	0.3˜0.7
A_l	0˜0.3

Establish situation indexes, training samples of expected situation BPA and prediction of expected situation BPA according to BPA construction principles. Train the back propagation neural network by using the mapping relations between situation indexes and expected output situation BPA in samples, to give it the prediction ability for situation BPA. When inputting situation indexes again, situation BPA can be outputted through formula (4).

3.3. D-S Evidence Combination / Situation Assessment

D-S evidence theory takes each integration as that of evidence situation BPA based on point in time. During situation assessment, each integration is taken as evidence integration based on point in time, when each evidence consists of situation status BPA based on point in time, and each situation status corresponds to one evidence statement. Algorithm of the integration is: the n-1 evidence is situation BPA of back propagation neural network at Tn-1 time. When producing the n evidence, it is integrated with the n-1 evidence, and then a piece of new evidence is acquired. Combine these evidence in sequence through Dempster integration formula, the final situation BPA can be acquired, and conduct the situation assessment of slope safety according to previously given decision logic. The workflow is as shown in Figure 2.

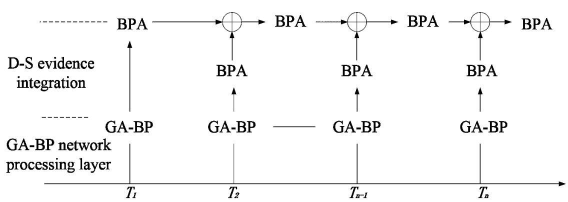

Fig. 2. Integration workflow of D-S evidence based on time domain

“ ” in Figure 2 represents the Dempster combination of situation BPA at different points in time, and GA-BP means the optimized algorithm of back propagation neural network based on GA.

4. Simulation Case

To verify effectiveness and feasibility of above-mentioned method, build experiment environment according to proposed situation index parameters. ARAMIS M/E microseism monitoring system from EMAG Group in Poland is adopted for microseism monitoring, software kit is stored in data center based on logs produced from quake events to be data source for situation assessment, and rainfall amount in the region recorded by water gauge and displacement information measured by GPS are served as data source for experiments. The experiment draws training set from original data source as test set. The training set contains sample input and corresponding expected output. Part of the input and output are shown in Figure 4.

Table 4. Sample input and output

Sample number	input			output		
	X1	X2	X3	N	A	θ
1	375	2800	1	0.20	0.70	0.10
2	390	2880	1.2	0.15	0.75	0.05
3	450	2720	1	0.30	0.65	0.05
4	270	2320	0.9	0.55	0.40	0.05
5	225	2160	0.7	0.65	0.30	0.05
6	480	2400	1.5	0.25	0.70	0.05
7	300	2480	0.6	0.45	0.50	0.05
8	330	2720	0.8	0.45	0.50	0.05
9	435	2976	1.6	0.10	0.80	0.10
10	495	2640	1.5	0.20	0.75	0.05

After data collection, input situation index parameter X = { X1 X2 X3} as back propagation neural network, and the output is BPA of situation status { N,A, θ} to be assessed and identified. The development curve of its training errors is as shown in Figure 3.

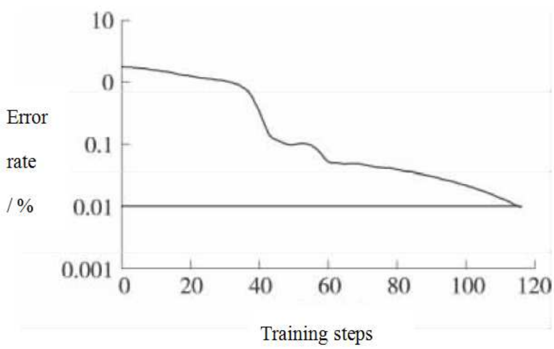

Fig. 3. Development curve of neural network errors

BPA value prediction is to conduct BPA predictions on GA-BP algorithm, traditional K-means clustering algorithm and back propagation neural network algorithm respectively, and compare each algorithm's performances and prediction results, which are as shown in Table 5 and Figure 4.

Table 5. Compare among algorithm performances

Algorithm	Iteration times	Mean square error
GA-BP	105	0.0010
K- mean	175	0.0018
BP neural network	260	0.0035

Table 5 gives the compare results among three different algorithms in iterations and mean square errors, and it is concluded that GA-BP algorithm is superior to other two algorithms in aspects of convergence speed and mean square error.

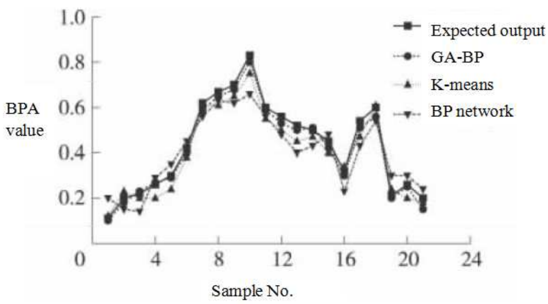

Fig. 4. Compare among prediction results of BPA values

Figure 4 gives the prediction curves of three algorithms' BPA values. GA-BP algorithm is superior to other two algorithms in prediction accuracy of BPA value, and its imitative effect is satisfactory. During BPA construction, GA-BP algorithm can reduce errors and improve convergence speed and prediction accuracy of BPA value. According to situation index parameters, GA-BP algorithm outputs the BPA of situation status { N,A,θ} corresponding to point in time T in order.

In phase of D-S evidence integration and situation assessment, use Dempster combination formula to integrate the situation BPA outputted from processing layer of GA-BP neural network in chronological order to acquire the situation BPA of the final evidence. It is as shown in Table 6, where it can be seen that with the situation BPA of each point in time continuously integrating, BPA of unknown situation θ decreases to 0.0410, and BPA value of abnormal situation A increases to 0.9578. The current situation is considered to be abnormal according to decision logic. The decision logic adopted here is the maximum Bel method, and it means the largest situation BPA, differences of which with other situation BPA are within regulated threshold, and the situation type is situation status. The experiment shows continuous integration of situation BPA at many points in time gives BPA better peak performance and identifiability, so as to reduce uncertainty in situation assessment.

Table 6. BPA of integration situations based on points in time

T	N	A	Θ
t1	0.1565	0.5344	0.3091
t1 + t2	0.0342	0.7781	0.1877
t1 + t2 + t3	0.0802	0.8201	0.1027
t1 + t2 + t3 + t4	0.0165	0.8879	0.0985
t1 + t2 + t3 + t4 + t5...	0.004	0.9578	0.0410

To guarantee effectiveness of the method proposed in this article and according to requirements for situation indexes, imitative artificial rainfall and disturbance are conducted to an open pit slope to make situation assessment of slope safety, and complete situation identification. Suppose the assessment period is 4h, and situation status can be identified according to the situation index data within the collection period. Meanwhile, organize many experts in mine safety to make actual assessment to current situation to verify the mentioned situation assessment method for slope safety. Then compare its situation recognition rate with that of the assessment method based on D-S. The results are as shown in Figure 5.

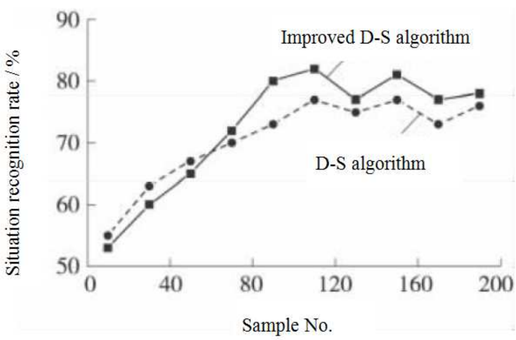

Fig. 5. Compare between situation recognition rates

Figure 5 compares the situation recognition rates between two algorithms. According to the results, it is concluded that the algorithm of landslide situation assessment based on improved D-S evidence theory is basically superior to that of the assessment algorithm for traditional D-S evidence theory in situation recognition. The experiment shows the situation assessment method for slope safety based on improved D-S evidence theory improves the objectivity and situation recognition rate of situation assessment results of slope safety by introducing GA and back propagation neural network.

5. Conclusion

The situation assessment method for slope safety based on improved D-S evidence theory proposed in this article solves such problems as dependent on expert experience, slow convergence speed and local minimum in BPA construction through optimized back propagation neural network by GA. On this basis, it is combined with D-S evidence theory and reduces the uncertainty in assessment through continuous integration so as to improve the situation recognition rate and complete the situation assessment of slope safety. Simulation cases show that the method is feasible and effective in situation assessment of slope safety. Combining of D-S evidence theory and other algorithms not only meets the complementary property of information integration, but also gives full play of merits of each assessment method, complementing each other's advantages. Combining different assessment methods is the development trend of situation assessment, which is of great significance to situation assessment of open pit slope safety.

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