ROCKBURST PREDICTION BASED ON NEURAL NETWORKS①

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ABSTRACT

Rockburst possibility prediction is an important activity in many underground opening design and construction as well as mining production. Insufficient knowledge, lack of characterizing information and noisy data restrain the rock mechanics engineers as well as mining engineers from achieving optimal prediction results. In this paper the authors present a novel approach to predict probable rock bursts in underground openings. The approach is based on learning and adaptive recognition of neural networks and allows input infomation to be incomplete, vague qualitative and noisy. The predicion task is carried out by two neural network subsystems in cascade. First a neural network is used to predict intensity and location of probable rock bursts. Next, another neural network uses this predicition and other geological features to identify the practical measures for prevention and mitigation of rock bursts. The experimental results on 10 cases show that a rockburst prediction accuracy of 100% was reached with constructed two neural network subsystems.

Key words: rockburst prediction neural network

1 INTRODUCTION

Most of the catastrophes in underground coal mines and hydroelectric tunnels are caused by rockbursts. Severe rockbursts appeared to have been accompanied by the throw of blocks, platelets and slabs which may have a weight of many tones and by the upwards bending of the floor with fissures of several cm width[1]. Rockbursts often occur suddenly when there is not enough time to reinforce surrounding rocks. If not properly treated they will deteriorate the stability of openings, the safety of field workers, and even cause serious accidents[2]. Therefore, prediction of the possibility of rockburst occurrence and its control are important activities in underground openings.

Great strides have been made over the last few decades in this field. Russens has suggested a classification scheme to estimate the intensity of rockbursts. Kidybinski (1981) has suggested a bursting liability index of coal to classify the occurrence and intensity of rockbursts into three classes. Tan[3] has introduced a fuzzy method to characterize uncertain data in rockburst prediction. Some researchers (e.g. Tan[1], *et al*.) have applied numerical analytical techniques to calculate the location of rockburst occurrence, and so on. It is doubtful, however, that for most geologic conditions there

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will even be the capability to describe a geologic environment or to fully simulate the complexity of mechanical response in a natural system[4]. In such an environment, the geological models had to be simplified and only several main factors instead of the whole set are considered as variables to set up a function. Therefore, the actual situations are variance from the predicted results from these kinds of models because of simplified processing. Insufficient knowledge of geological features and lack of characterizing information restrain these reported approaches from achieving optimal results. A noisy version of the cues may lead to a wrong prediction or failure in predicting.

A more suitable technique for handling this prediction problem is machine learning and recognition based on neural networks. A neural network is an intelligent information processing system, with high nonlinear dynamic features and considering various governing factors as a whole without limiting their quantity, by means of simulating working ways of man's nervous system such as performance of perception recollection, learning and reason. In the retrieving process of neural networks, even if the features used to describe the pattern are vague or imcomplete, this does not cause any difficulty in most situations. Neural networks have the potential to acquisit uncertain knowledge from case histories and generalize to solve similar problems.

In this paper we describe a novel approach to rockburst prediction problem using machine learing and recognition based on neural networks. The neural network prediction system thus eatablished can let a geotechnical designer quickly access previous experience with similar excavations and identify the most likely locations and intensities of rockburst occurrence together with the key geological features which affect these rock bursings. In our network system, two neural networks are performing in cascade as components: a neural network is first used to predict location and intensity of rockburst occurrence, and then another neural network that uses this predictions and other geologic features predicts measures to prevent and control this probable rockburst.

2 NEURAL NETWORK LEARNING FROM CASE HISTORIES

Our method of rockburst prediction is performing based on learning and adaptive identification of neural networks. The prediction of the occurrence and intensity of rock bursting is implemented in two phases. First a neural network learning engine was constructed to learn knowledge from case histories and contributed them on various interconnections of the trained networks. Next, a neural network recognizer performs associative and adaptive identification of the location and intensity of rockburst occurrence by matching the pattern of the case at hand with those patterns of geological features and behavior of excavations in the trained network and retrieving the similar ones in a very short period of time. This identification procedure based on neural network learning is shown in Fig. 1.

2.1 *Neural Network Model*

Inspired by neurologic investigations, neural network models have been developed to attempt to the nervous system and achieve a human-like perfomance in many disciplines. These models are composed of many nonlinear computational elements operating in parallel and arranged in patterns reminiscent of biological neural net. Fig. 2 illustrates the basic aspects of a neural net.

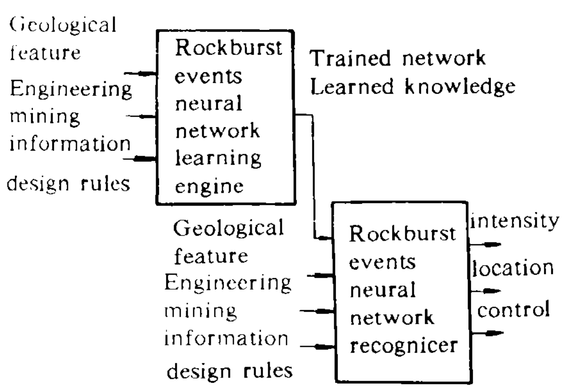

Fig. 1 Learning and adaptive identification of neural networks for rockburst prediction system

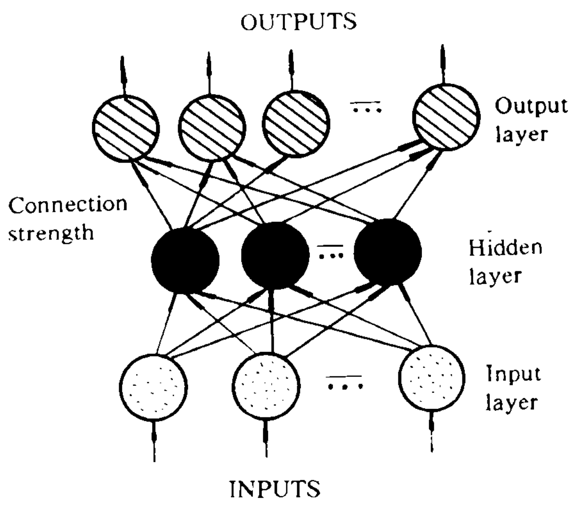

Fig. 2 A multilayer feedforward neural network

Neural network models are specified by the topology of the network, the characteristics of the nodes (i. e. nerves) and the processing algorithm (learning rules). The intelligent information properties of a neural network arise from the above specifics. The topology of a multilayer neural network consists of several distinct layer of nodes (neurons) including an input layer and an output layer. The nodes in the input layer are receiving inputs from the outside world. The nodes in the output layer are activated in a pattern which responds to specific input patterns. Between the input layer and the output layer we have one or more layers of nodes which are called hidden. The nodes in the hidden layers, called hidden nodes, are used to represent domain knowledge useful for solving recognition tasks. Generally, each node in one layer is interconnected with all the nodes in adjacent layers with connections, known as synapses. Each connection is associated with a weight W_{ij} which measures the degree of interaction between the corresponding nodes.

$$W_{ij}\begin{cases} >0 & \text{If node } u_j \text{ excites } u_i \\ =0 & \text{If node } u_j \text{ has no direct} \\ & \quad \text{connection to node } u_i \\ <0 & \text{If node } u_j \text{ inhibits node } u_i \end{cases}$$

During a learing stage the weights are adapted to simulate the changing conductance of natural synapses.

2. 2 *Neural Network Learning Algorithm*

Being different from the conventional learning, neural network learning take place when weights are adjusted. The goal of learning is to minimize the error between the desired outputs (target) and the actual outputs of the network. The learning is conducted by the back- propagation algorithm[4]. Back-propagation learning, more precisely described as steepest descent supervised learning using back-propagation of error, is making an initial estimation of weights and then repeated revisions will be made based on gradient descent operating. This learning is terminated either whenever the total sum of the squared errors between target and computed output was minimized or when all patterns produced the desired output with a predefined acceptable error margin.

2. 3 *Improvement of Generality of Network Learning Algorithm*

The following improving measures were adopted to achieve better convergence rate and generality for back- propagation learning in our rockburst prediction system.

(1) Two-Level Networks

With decomposition of rockburst prediction task, two networks were constructed in cascade as components of the whole prediction system: rockburst possibility prediction neural network (RPPNN). and rockburst prevention measure identification neural network (RPINN). RPPNN predicts the location and intensity of rock bursting, and this is fed together with other features to the RPINN to produce the prediction of measures of controlling rockbursts. A block diagram of two- level networks for rockburst prediction system is shown in Fig. 3.

This cascading processing overcomes the construction of more complex network so that the system has achieved good convergence rate and adaptation. This emphasises the fact that methods of controlling rockbutrst should correspond to the intensity of probable rock bursting as well.

(2) Afferent and Efferent Transformation

The data dealed in rockburst prediction tasks include qualitative representations and numerical values. The qualitative representations were transformed into numerical values which the network can accept by using a constructed afferent rule. For example, limestone in lithological type defined as 1, sandstone defined as 2 and so on. The normal output is in [0,1]. An inverse transformation based on efferent rule was performed to translate this normal outputs in [0,1] into what we wanted to express. This afferent and efferent processing may bring many geological factors and qualitative engineering/mining informatio into network learning and identification without any difficulty.

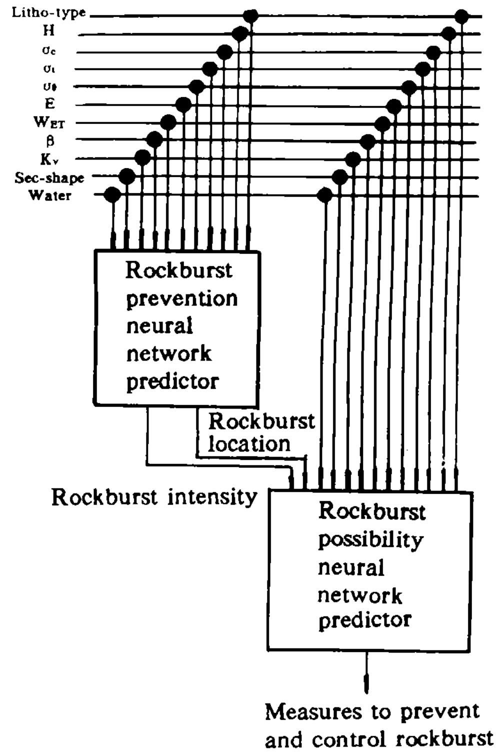

Fig. 3 Block diagram of two-level neural networks for rockburst prediction system

(3) Normalization of Input Data

The normal inputs of network are between 0 and 1. Note this process will impose a limit of the maximal size of input data. This limitation is not desirable and may be overcome by normalizing the data to very large values of features.

The formula is written by

$$X_{ik} = \frac{X_{ik} - \min\limits_{j}(X_{ij})}{\max\limits_{p}(X_{ip}) - \min\limits_{j}(X_{ij})} \qquad (1)$$

$$(i = 1, \cdots, m; k = 1, \cdots, n)$$

where m is the dimensions of the input vec tors, n is the number of samples.

(4) Suitable Network Architectures

The performance of neural network recognition is related to the topology of the network. Once the number of neurons on the input layer and output layer was designed for a specific task the performance of network is affected by the number size of hidden layer. Many number of hidden layer and many number of nodes per hidden layer were evaluated to gain better performance.

Weights of connections between two nodes in adjacent layer are referred to as hard weights or soft weights. The hard weights are defined to be 0 to indicate that they are a fixed or " hard-wired" part of the architecture. These hard connections indicate that there is no inference between two nodes. The soft weights, used as the representation of domain knowledge, have the potential for modification during learning. The size of soft weights represents connection strength between nodes.

2. 4 *Learning Knowledge From Case Histories*

More than 201 case histories have been collected from 25 underground coal mines and hydroelectric tunnels in China and used as learning patterns. The openings were chosen so as not to bias the network toward any sectional shapes (circle, semi-circle arch + straight wall, horse-shoe etc.) or excavation type (hydroelectric tunnel, gang-way in coal mine, extraction drift etc.). Features are extracted from learning patterns and used to train two multilayer networks using gradient descent. The network structure adopted is shown in Fig. 4.

The inputs to the rock burst possibility prediction neural network are the following:

Litho-type—Lithological type;

H —Overburden of underground openings;

σ_c —Uniaxis comprehensive strength of rock;

σ_t —Tensile strength of rock;

σ_0 —Tangential stress of rock surrounding openings;

E —Young's modulus;

W_{ET} —Elastic energy index of surounding rocks, which is the elastic-energy-to-dissipated-energy ratio;

β —Separation angle between the strike of main joint set and maximal principal stress;

K_v —Intact coefficient of rockmass;

Sec-shape—Sectional shape of underground openings;

Water—Groundwater conditions (dry, wet, minor inflow (< 5L/min), medium inflow etc.).

The inputs to the RPINN are both the inputs and the outputs of the RPPNN. It is interesting to note that the content of these parameters will be expanded with further understanding of rockbrurst mechanism and the further analysis of more case histories.

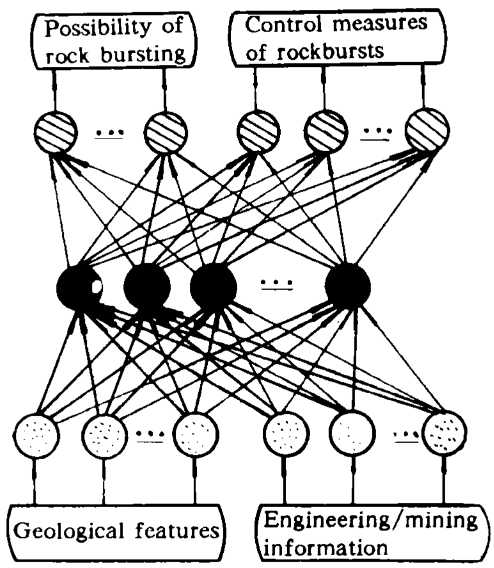

Fig. 4 The Structure of rockburst prediction and control neural network

The outputs of the RPPNN and the RPINN are two ploting- point values between 0 and 1 representing the predicted location and intensity of rockbursts and their prevention measures respectively.

At learning stage, each pattern is first randomly presented to the system as input and target vectors. and then the repeated representation of each pattern is done with successive adjustment of weights. Learning is terminated when all learning patterns produced target patterns which fell within a margin. Knowledge thus learned are represented by stable weights and topology of networks for the use of the network recognizer in evaluating new sets of inputs and analysing new patterns.

3 NEURAL NETWORK RECOGNITION

Here, we make use of the capability of neural networks to generalize to predict the possibility and prevention measures of rockbursts which have no seen previously using knowledge learned from learning patterns. This prediction procedure is also called associative inferrence and adaptive recognition operated by trained neural networks.

New case records, which total 10, are collected to be used as recognizing patterns of the network recognizer. Features of these patterns are shown in Table 1 and presented to the system as inputs. The possibility of rockburst occurrence recognized by the RPPNN is given in Table 2. On the basis of recognition of probable rock bursting the RPINN suggests some practical methods for prevention and mitigation of rock bursts (see Table 3). The identifying results showed that a rockburst prediction accuracy of 100% was reached with these two neural network recognizers.

Table 1 Data Of Cases Used As Inputs Of The Network Recognizer

Cases	Lithological type	Overburden /m	σ_c / MPa	σ_t / MPa	σ_θ / MPa	$E\times10^4$ /MPa	W_{ET}	β	K_V	Section shape	Groundwater inflow
1	Dolomitic limestone	225	88.7	3.7	30.1	5.6	6.6	10	0.93	Circle	Dry
2	Sinaite	194	220.0	7.4	90.0	5.9	7.3	10	0.85	Circle	Dry
3	Granite	375	171.5	6.3	18.8	5.7	7.0	45	0.60	A*	Wet
4	Limestone	435	149.0	5.9	34.0	6.5	7.6	75	0.63	Circle	Minor inflow
5	Clay sandstone	250	53.0	3.9	38.2	1.2	1.6	89	0.80	A*	Minor inflow
6	Marble	100	90.0	4.8	11.3	5.3	3.6	75	0.79	A*	Dry
7	Limestone	300	263.0	10.7	92.0	7.9	8.0	11	0.93	Circle	Dry
8	Diorite	330	235.0	9.5	62.4	7.2	9.0	15	0.87	Circle	Dry
9	Granite	223	136.5	7.2	43.4	3.4	5.6	21	0.93	A*	Dry
10	Diastatite anorthose	425	105.0	4.9	11.0	9.7	4.7	58	0.75	A*	Wet

A* = Barrel vault and line wall

Table 2 The Possibility Of Rockburst Occurrence Recoginzed by The RPPNN

Descriptions		Degree of activation									
		Case 1	Case 2	Case3	Case 4	Case 5	Case 6	Case 7	Case 8	Case 9	Case 10
1 Location	Centre of crown	0. 001	0. 000	0. 000	0. 000	0. 000	0. 000	0. 003	0. 993	0. 987	0. 000
of	Left of crown	0. 007	0. 009	0. 001	0. 000	0. 000	0. 000	0. 975	0. 007	0. 001	0. 000
rockburst	Left of crown and its symmetric place	0. 998	0. 989	0. 000	0. 000	0. 000	0. 000	0. 009	0. 998	1. 000	0. 000
	Springline	0. 003	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 001	0. 000
	Above spring-line	0. 000	0. 001	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000
	Right of foot-arch	0. 000	0. 007	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000
	Foot-arch	0. 000	0. 005	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000
	Enter section	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000
2 Rockburst	None	0. 000	0. 000	1. 000	0. 000	1. 000	0. 998	0. 000	0. 000	0. 000	1. 000
intensity	Light	0. 000	0. 000	0. 000	0. 997	0. 001	0. 003	1. 000	0. 008	0. 003	0. 000
	Moderate	0. 009	0. 001	0. 000	0. 003	0. 000	0. 000	0. 003	0. 008	0. 003	0. 000
	Heavy	0. 999	1. 000	0. 000	0. 009	0. 000	0. 000	0. 000	0. 995	0. 989	0. 000

Table 3 Practical Methods For Prevention And Mitigation Of Rockbursts Suggested By The RPINN

Rockbust control	Degree of activation					
	Case 9	Case 2	Case 3	Case 4	Case 7	Case 8
Water infusion	0. 000	0. 000	0. 000	0. 000	0. 000	0. 000
Auger driling	0. 998	0. 998	0. 000	0. 999	0. 001	0. 999
Auger drilling+ permissible explosives	0. 003	0. 031	0. 000	0. 000	0. 991	0. 000
Bolt	0. 007	0. 001	0. 993	0. 001	0. 000	0. 000
Shotocrete	0. 000	0. 001	0. 931	0. 003	0. 010	0. 009
Bolt-web-shotcrete	0. 973	0. 993	0. 009	0. 000	0. 021	0. 945

4 CONCLUSIONS

We have presented a novel approach to solve complex problem of predicting probable rock bursts. Our approach is based on ma chine learning by nerual networks. It makes use of the capability of neural networks to generalize. The predicition task is carried out by two neural network subsystems in cascade as components; The RPPNN predicts intensity and location of probable rockbursts. The RPPNN uses this prediction together with another geological features to identify practical measures to prevent and mitigate probable rock bursts. This system has been implemented as the first stage of an opening assistance design system. The system is written in a high-level computer language, which is called GCLISP.

A more important features of this system is that it is capable of continuously learning of adaptation by adding new data to the existing data set and retraining. This capability is very important for complex rock mechanics problem solving, particularly, when input data is limited and new geological conditions are continuously encountered. Furthermore, employing this learning approach can reduce the difficulty of problem solving in complex rock mechanics environment where insufficient knowledge often occurs and that of knowledge acquisition.

Another more important feature of this system is its content- addressability. This property is valueable for the domain of data-limited rockburst prediction and rock opening design because it can help designer determine default values of geologic features and correct incorrect parts of the content of a pattern.

The identification of probable rockburst of new cases is made by adaptive and associative reason of neural networks. The degree of activation of an output node of a certain neural network generated by the system reflects quantitatively its relative importance. This property will allow predictors to quickly assess the best suitable measures of controlling rockbursts or the controlling parameters for further detailed analysis.

Furthermore, to the best of our knowledge this has been the first attempt at predicting the possibility of rockburst occurrence using machine learning based on neural networks. We will need to consolidate our results by further testing on a larger test set.

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(*From page 6*)

be convenient to the user, but also decrease the calculation cost greatly.

(3) For the Xishimen Iron Mine, the optimum panel mining sequence at the objecitve of rock mechanics is : Panel Ⅱ front to Panel Ⅲ, Panel Ⅲ front to Panel Ⅳ, Panel Ⅳ front to Panel Ⅴ, which form the benched working line that is oblique to the strike of the orebody.

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