Artificial Neural Network Method of Rock Mass Blastability Classification

Jiang Han, Xu Weiya, Xie Shouyi
Research Institute of Geotechnical Engineering, Hohai University, Nanjing, Jiangshu, P.R.China 210098
E-mail: flmao@sina.com

Abstract

Considering the practice of rock engineering, an attempt has been made to implement artificial neural network (ANNS) for the concept and method of rock mass blastability classification. A set of rock mass blastability data has been used for neural network training and testing. The model classification technique based on ANN has been used to classify the rock mass blastability rank. The better ANN model for rock mass blastability classification is given and described after the ANN training and optimizing. The given ANN model is effective and of good stability and adaptability when used to give the result of rock mass blastability classification. It is concluded from this study that the ANN-based rock mass blastability classification can be developed well by proper training and learning algorithms based on a comprehensive data set, and the different importance of every influencing factor can be directly got from its different net-weight.

1. Introduction

The designing and processing of rock blasting engineering is dependent on the result of rock mass classification. Obviously, different methods should be used for different rank of rock mass. It is very important to give a practical and reasonable way to classify the blastability of rock mass.

Rock mass, as an indefinite matter, is a comprehensive engineering object. Its characteristic is mainly controlled by the structure plane and structure of rock mass. The environmental condition of rock mass and geologic condition have definite influence of the rock blasting. The traditional rock mass classification methods, only focused on rock itself, use some isolated indexes which consider no characteristics of blasting engineering but of rock mass. In fact, many factors may affect the rock-blasting behavior besides the characteristic of rock mass. It is obviously very difficult and even impossible to control the entire factor, which would affect the behavior of rock blasting engineering. The reasonable method of blastability classification, whose object is to direct the rock blasting engineering, is not only to reveal the characteristic of rock mass but also to predict the quality of blasting engineering.
Artificial neural networks, is discussed in this paper to classify the blastability of rock mass. This method will be applied in practical cases of rock blasting engineering for classify the rank of rock mass blastability.

2. Artificial neural networks

2.1 Definition of artificial neural networks

Many publications have introduced the knowledge of artificial neural network. According to Haykin, S., Nigrin, A. and Zurada, J.M.\textsuperscript{[1,2,3]}, artificial neural network is a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. It is a circuit composed of a very large number of simple processing elements that are neurally based. Each element operates only on local information. Furthermore each element operates asynchronously; thus there is no overall system clock. It resembles the brain in two respects:

1. Knowledge is acquired by the network through a learning process.
2. Interneuron connection strengths known as synaptic weights are used to store the knowledge.

Artificial neural networks is a physical cellular system which can acquire, store, and utilize experiential knowledge. Basically, a neuron is a black box that excels in solving problems of pattern recognition and identification, classification, pattern association, function approximation, forecasting and prediction, and search and optimization (well-established characteristics of humans). Therefore, artificial neural networks is capable of the classification of rock blasting theoretically. Artificial Neural Networks are usually made-up of a number of simple, highly interconnected processing elements (PE's) or neuroses. PE's emulate our understanding of the biological neuron that is "thought" to be the building block of the animal brain. Artificial neural networks consist of simple, highly interconnected, parallel processing elements also called nodes or neurons. All signals that arrive at each node are processed and transformed so that they can be transmitted to another node. The encoding of information in the network is achieved during the learning (or training) phase, which can be can be supervised, unsupervised or reinforced. This takes place when the network modifies its internal parameters, particularly its synaptic weights, in response to external stimuli.

2.2 Backpropagation neural networks

Backpropagation (BP), a euphemism for the generalized delta rule including momentum, is a supervised learning algorithm that applies to non-linear, multilayer, feedforward structure of nodes (networks). It works on minimizing the Mean Square Error, MSE, of the network.

Backpropagation refers to the method for computing the gradient of the case-wise error function with respect to the weights for a feedforward network, a straightforward but elegant application of the chain rule of elementary calculus. Basically, it requires no
rules, no equations, and no conventional programming. It can be highly efficient for some large data sets via self-organizing, learning, and forgetting.

The architecture of a BP network refers to the way it decodes information, that is the direction of information during recall. In a BP neural network the nodes are organized in input, hidden, and output layers, as Figure 1.

![BP neural network diagram](image)

Figure 1 a BP neural network.

Training of a BP neural network is achieved by presenting inputs to the network with the desired outputs. The network processes the inputs into its own simulated outputs. Input layer neurons, some time called as processing elements (PE's), receive the data to be processed by the network and the output layer holds the global computation results. One or more hidden layers may be present depending on problem complexity but quite often one layer suffices. All PE's within the input layer are connected to all PE's of the first hidden layer. These are subsequently connected to all PE's of the second hidden layer, if one is present, or to the PE's of the output layer. A weighting factor is associated with each connection. The same process is repeated with all adjacent hidden layers until the input layer is reached. At that moment all synaptic weights are updated. As neural networks are trained on sample data, these should be of high quality and representative of the domain.

3. Parameters of blastablity classification and neural networks

3.1 Parameters of rock mass blastablity classification
The fragmentation of rock blasting is mainly along the fissuring, microfissuring and soft stratum. The characteristic of fragmentation, in some senses, is decided by the geological structure of rock mass. The practices of blasting operations have proved that the characteristic of rock mass has more influence to the result of rock blasting than explosive does. The factors influencing the characteristic of rock blasting can be divided into three groups: the structure of rock mass, the strength of rock, the characteristic of fragmentation.

Normally, the structure of rock mass has more influence to rock blasting than the characteristic of rock itself does. The degree of denseness of soft stadium has considerable influence to the result of rock blasting. The strength of soft stadium is so much lower than that of rock that the rock mass can be considered as rock blocks which have been incised by soft stadium before the blasting. When blasting is operated in the rock mass which include dense soft stadium, the explosive air can easily escape to less the fragment energy. In this paper, the distance and length of fissures is used to represent the characteristic of structure of rock mass.

The strength of rock decide the difficulty degree of blasting. It is obvious that soft rock is easier to break up that hard rock. The strength parameters include compress strength, tensile strength, shear strength and elastic modulus etc. As for the rock blasting, the dynamic compress strength and dynamic elastic modulus is the important parameters to represent the dynamics characters of rock strength.

The characteristic of rock fragmentation can be described by the blasting distribution of block. Practically, the demand to fragmentation distribution is different when different operating and transporting equipment are used. In this way, we can say the difficulty degree of blasting operation is different too. The percentage of unqualified block and mean fragmentation size are used here to represent the characteristic of rock fragmentation.

3.2 Computation mode of ANN

The computation mode of rock mass blastability classification is given as followed equation:

\[ K = \{L, S, R_{cd}, E_{d}, P_{c}, d_{cp}\} \]

There are 6 input parameters, representing the structure of rock mass, the strength of rock and the characteristic of fragmentation, are used to train the network.

L: the total length of fractures in 2x2m² block,
S: the mean distance of fractures in 2x2m² block,
R_{cd}: the dynamic compress strength of rock,
E_{d}: the dynamic elastic modulus of rock,
P_{c}: the percentage of unqualified block
\(d_{cp}\): mean fragmentation size
The output parameter of network is K, the rank of rock mass blastability classification.

These data are used to develop a neural network designed to evaluate the rock mass blastability classification. In this work a back-propagation network is used which has 6 input PE's, 5 hidden PE's and 1 output PE's. The structure and factors of final network are achieved by times of optimizing computation. Other forms of networks don't show the same degree of success in network training and generalization.

4. Example and test

4.1 Database of ANNs

Based on the data\textsuperscript{[4]}, the study of rock mass blastability classification has been made. 88 data set representing different blasting conditions are used to construct the vector space of networks. 44 sets as training data, 22 as validating data and 22 as testing data are chosen randomly.

L and S are measured in 2x2m\textsuperscript{2} block at the middle line of blasting sidestep. Rcd and Ed are gotten from the Split Hopkinson Pressure Bar Test, Pc and dcp are gotten by visual comparing of standardized photograph.

An expanded database incorporating more input, in turn would provide for a more complete adaptability of the network. It is also true that the precision of rock mass blastability classification will be improved at the same time.

4.2 Test result

These training data and validating data are used to train and validate the neural networks. The structure and factors of networks are achieved when minimal Mean Square Error (MSE) is satisfactory after times of optimizing computation. The test data is used as the qualifying vector to test the generalization capacities of the optimal networks. Some result of rock mass blastability classification is shown in Table 1. Thanks for the learning and adaptability of ANNs, The difference between the real and testing K values is under 10%. The result is acceptable.

<table>
<thead>
<tr>
<th>L(m)</th>
<th>S(cm)</th>
<th>R_{cd} (Mpa)</th>
<th>E_{d} (Gpa)</th>
<th>P_c (%)</th>
<th>d_{cp} (mm)</th>
<th>K(real)</th>
<th>K(testing)</th>
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<tr>
<td>8.89</td>
<td>63.34</td>
<td>235.00</td>
<td>64.00</td>
<td>0.56</td>
<td>352.00</td>
<td>3</td>
<td>2.99</td>
</tr>
<tr>
<td>7.43</td>
<td>73.00</td>
<td>235.00</td>
<td>64.00</td>
<td>0.23</td>
<td>234.00</td>
<td>3</td>
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<tr>
<td>9.12</td>
<td>24.00</td>
<td>135.00</td>
<td>44.00</td>
<td>0.46</td>
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<tr>
<td>9.89</td>
<td>11.34</td>
<td>135.00</td>
<td>44.00</td>
<td>0.39</td>
<td>200.00</td>
<td>1</td>
<td>1.05</td>
</tr>
</tbody>
</table>
Table 1 result of rock mass blastability classification by ANNs

The weights of different input parameters in networks are listed in Table 2. It can be found that the structure of rock mass, which commonly is considered as the important influencing factor of rock blasting result, has comparative smaller weight than other factors. Meanwhile, the length and distance of fractures which represent the structure of rock mass, and the percentage of unqualified block and mean fragmentation size which represent the characteristic of fragmentation, have prominent result to rock mass blastability classification.

<table>
<thead>
<tr>
<th></th>
<th>L(m)</th>
<th>S(cm)</th>
<th>$R_{cd}$ (Mpa)</th>
<th>$E_d$ (Gpa)</th>
<th>$P_c$ (%)</th>
<th>$d_{cp}$ (mm)</th>
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<tr>
<td>PE1</td>
<td>3.62</td>
<td>15.70</td>
<td>-4.08</td>
<td>-6.77</td>
<td>8.06</td>
<td>1.87</td>
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<td>-6.68</td>
<td>4.80</td>
<td>3.93</td>
<td>3.21</td>
<td>4.56</td>
<td>2.55</td>
</tr>
<tr>
<td>PE3</td>
<td>-3.66</td>
<td>8.21</td>
<td>1.47</td>
<td>-7.00</td>
<td>5.36</td>
<td>1.73</td>
</tr>
<tr>
<td>PE4</td>
<td>-0.80</td>
<td>-8.67</td>
<td>-6.14</td>
<td>-0.05</td>
<td>7.22</td>
<td>-9.42</td>
</tr>
<tr>
<td>PE5</td>
<td>-0.92</td>
<td>1.12</td>
<td>-0.00</td>
<td>0.39</td>
<td>-0.61</td>
<td>-1.22</td>
</tr>
</tbody>
</table>

Table 2 the weights of different input parameters in networks

5. Conclusion

A neural network prototype has been successfully developed in this paper to classify rock mass blastability. The prototype network has a feedforward structure and is based on the BP learning paradigm. The input-vector consists of six elements characterizing the structure of rock mass, strength of rock and fragmentation degree of blasting. The network output is a single vector denoting rank of rock mass blastability classification.

Artificial neural network is a new method applied to rock mass blastability classification. Because of its flexibility and generalization, the error of individual sample data has little influence on final result. Network training, testing, and production was relatively fast, reliable, and efficient. This method is easy to handle and can be used in practical rock blasting engineering conveniently.

References

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