Quantitative evaluation of coal-mining geological condition

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Abstract

With the development of modern coal industry, it is a growing attention to evaluate coal-mining geological condition in the world's major coal-producing countries. This study proposes an Artificial Neural Networks (ANN) model that was constructed by ten significant factors using back-propagation (BP) algorithm. These factors include (1) fault throw, (2) fault density, (3) fault intensity, (4) fracture fractal dimension, (5) coal thickness, (6) abnormalities of coal thickness, (7) coal structure, (8) coal dip, (9) change of floor elevation, (10) combination of rock. The optimizing division method and the inserted-value method were used to establish samples for network training, and the structure of input, hidden and output layers of BP network was optimized. A total of 15 potential cases collected in Dongpo Mine were fed into the ANN model for training and testing. Achievement predicting 27 unknown units demonstrates that the presented ANN model with ten significant factors can provide a stable and reliable result for the prediction of coal-mining geological condition in hazard mitigation and guarding systems. The results show that it is effective in evaluating the unknown units for the trained network.

Keywords: Coal-mining geological condition; artificial neural networks; back-propagation; training samples; quantitative evaluation

1. Introduction

With the increased level of modernization of the coal industry, attention to coal-mining geological evaluation is growing in the world's major coal-producing countries. Compared with other countries, coal occurrence conditions is more complex in China, exploration data alone cannot meet the construction

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**Keywords:** Coal-mining geological condition; artificial neural networks; back-propagation; training samples; quantitative evaluation
needs of high-yield and efficient mine. Therefore, quantitative evaluation and prediction of the geological conditions of coal-mining before mining has an irreplaceable role [1], which is the one of based approach and the necessary means for high-yield and efficient mining-work-face, and is guiding condition for further geophysical work.

Evaluation of geological conditions of coal-mining is developed by the qualitative analysis to quantitative evaluation; the theories of nonlinear science have gradually applied to them. This paper introduced artificial neural network method in the evaluation of geological conditions of coal mining applications for Dongpo Mine, Tongchuan Mine, Shaanxi Province, China.

2. Influence Factors of Geological Condition

Dongpo Mine in the eastern of the Tongchuan Mine is the representative Coal in Shaanxi Province, China.

Taiyuan Formation in Upper Carboniferous is the main coal-bearing rocks, thickness 12 ~ 84m, usually 20 ~ 25m or so, coal-bearing layers 2 to 7, 5'2 coal is the main mining region layer, thickness of 2 ~ 3m. Roof of 5'2 coal is generally sandy mudstone directly, the thickness of 0 ~ 3m, upper roof is the bottom of the Shanxi Formation in coarse-grained gray sandstone, or sandstone, mudstone (K₄ sandstone), thickness 10 ~ 20m. Floor of 5'2 coal is generally mud, shale or sandstone. In the process of coal production, roof and floor of coal have yet to produce a direct threat. Hydrogeological conditions are relatively simple, more localized impact on coal production.

Dongpo Mine belongs to the low gas, low-high carbon dioxide mine, dust explosion index about 22%, no spontaneous combustion tendency of coal, ground temperature and other conditions, no obvious abnormalities.

Geological structure is the key to affecting the production of coal mining. In Dongpo Mine, addition to the mining structure other than the geological conditions are better, the main factor, affecting 5'2 coal mechanized mining, is the structure and changes in coal thickness controlling by the structure. The coal thickness, coal and its roof and floor rock characteristics and composition reflect different aspects affecting the mining and geological conditions, so structure index is selected to construct the main indicators in this evaluation.

(1) Fault throw
Fault throw measures the degree of fault development, Fault throw greater, and the relative degree of structure the more complex.

(2) Fault density
Fault density can be measured degree of fault development, defined as the number of faults within the unit area

\[ M = \frac{N}{S} \]  

where \( S \) is unit area; \( N \) is number of faults within the unit area.

Fault density is greater, indicating more intensive fault, and then the complexity of its structure is relatively higher.

(3) Fault intensity
Fault intensity is an indicator for measuring the degree of fault development unit, defined as the sum of product between fault length and the gap within unit area, that is

\[ F = \left( \sum_{i=1}^{n} H_i * L_i \right) / S \]  

(2)
in which $S$ is unit area; $H_i$ is the gap of the $i$-th fault; $L_i$ is the length of $i$-th fault falling into the unit area; $N$ is number of faults within the unit area.

Fault the greater the intensity, the more faults that developed in the unit, which is not conducive to coal mining.

(4) Fracture fractal dimension
Fracture fractal dimension [3] is an indicator made after introducing fractal geometry to evaluation system, which act as comprehensive reflection of the fault number, scale, combination, horizontal extension length and uneven distribution, can be used as a quantitative indicator of faults.

The complexity of structure in block section evaluating by similar dimension of fracture dimensional networks has Incomparable advantages compared with other indicators. Generally the method of number of grid can calculate the fractal dimension.

(5) Coal thickness
Coal thickness is the thickness of main coal mining in the study area, where a weighted average of all the drilling data is selected within the unit area.

(6) Abnormalities of coal thickness
It defines standard deviation of coal thickness as the abnormal limit of coal thickness in the region, and then determines whether the difference between coal thickness at the point and the mean of that in the region is beyond the scope of abnormal limit.

(7) Coal structure
Coal structure is defined as the number of coal. The fewer the number of coals, the simpler coal structure, the more conducive to mining.

(8) Coal dip
Coal dip is defined as the maximum visual angle of coal for all drilling in the unit area. Visual angle ($\alpha$) of coal at drilling point is expressed as the arcsine function of quotient between difference ($h$) with elevation of coal floor in drilling and elevation of coal floor in the center unit (obtained by the weighted average of all drilling in the unit) and the drilling horizontal distance ($d$) from the midpoint of the unit.

\[
    h = |z_i - z_k|
\]

\[
    d = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2}
\]

\[
    \alpha = \arcsin \left( \frac{h}{d} \right)
\]

where $x$ is horizontal coordinate of drilling; $y$ is longitudinal coordinates of drilling; $z_i$ is elevation of coal floor in drilling; $z_k$ is the weighted average of elevation of coal floor in all drilling.

(9) Change of floor elevation
Using of floor elevation observations of each control point to trend analysis, the trend value is got which is difference between of the actual measured value and the trend value of coal floor, called residual value of structure. Assuming structure interface is a plane, it is can be completely fit for a trend surface, the residual value of 0;Otherwise, there is the surplus residual value at the raised parts and negative at depressed area. The larger difference between actual structure interface and trend surface, the structure remaining value will be greater. Therefore, the residual value of structure is measure of deviation for the actual structure interface and ideal mathematical surface.

(10) Combination of rock
Combination of upper and lower rock referred to as a combination of rock types about "coal roof - coal - coal floor". Four categories can be divided into

A Weak rock - coal - weak rock, quantization parameter 1;
B Weak rock - coal - interbedded rock with strength and weak rock, quantization parameter 2;
C Interbedded rock with strength and weak rock - coal - weak rock, quantization parameter 3;
D Interbedded rock with strength and weak rock - coal - interbedded rock with strength and weak rock, quantization parameter 4.

The greater quantitative parameters, the higher stability for the combination of rock up and down the coal, and the more conducive to development for structure.

3. Grade of Mining Geological Condition

Grade of mining geological condition, with order-based data, presents differences of geological condition in different sections of the mine. According to the geological condition and the actual production of coal, coal-mining geological condition in Dongpo Mine can be divided into I, II, III three levels.

Grade I, thickness of 5\(^{\circ}\)-2 coal roughly has about 3m; the thinnest of not less than 2.5m, the structure is relatively simple. Thickness of coal under 5\(^{\circ}\)-2 coal is about 15m, and no dramatic changes. Sandstone K4 is the roof of coal, or it is very close distance to Sandstone K4. There are few faults and fault throw generally less than 2m, fracture similar dimension (D) [2] less than 0.9, and angle of coal less than 25 degree, no big "pit" development, no other abnormal geological phenomena in the coal.

Grade II, thickness of 5\(^{\circ}\)-2 coal is greater than 2m, relatively simple of the structure. Thickness of coal under 5\(^{\circ}\)-2 coal has no less sudden changes, where thickness of direct roof of coal is stable. Structure is more complex, which exist outside fault dense belt or structure belt, with 0.9 \(\leq D \leq 1.1\).There have greater changes of angle of coal, and sparser development of "pit".

Grade III, thickness of 5\(^{\circ}\)-2 coal is about 2m, or no less than 2m, and the complex structure. Thickness of coal under 5\(^{\circ}\)-2 coal has large or small, or mutation. Roof of coal is combined with strongly broken rocks. Structure is complex, with the development of small fault belt, layer slip belt and dip mutation, D> 1.1.

Grade I can be used as the preferred area for mechanized mining, grade II can be arranged as high-grade conventional mining area, or upgraded or downgraded through exploration, extraction, grade III areas should be arranged only blasting taken.

With the cell extraction from simple to complex for geological conditions, it will be found that value of evaluation index form in ascending or descending order of orderly geological variable. When all the evaluation of each unit have been quantified. The evaluation will be a corresponding range of different values for different units of mining geological condition. In order to find the correspondence between interval of continuous index value and grade of mining geological condition, the optimizing division is made for orderly geological variable.

4. Correspondence between Grade of Mining Geological Condition and Interval of Index Value

For Dongpo Mine, the optimal three-stage division is carried, according to its three levels of geological condition. Fractal dimension of each unit is sorted by ascending as \(x_1, x_2, \cdots, x_{n-1}, x_n\); after optimal three-stage divided, the optimal divided point is \(\alpha_1(n), \alpha_2(n)\), then the optimal three sections is divided into:

\[
\{x_1, x_2, \cdots, x_{\alpha_1(n)}\}, \{x_{\alpha_1(n)+1}, \cdots, x_{\alpha_2(n)}\}, \{x_{\alpha_2(n)+1}, \cdots, x_n\}
\]

Correspondence between index value of fractal dimension and grade of mining geological condition is taken as Table 1.
Table 1. Correspondence between index value of fractal dimension and grade of mining geological condition

<table>
<thead>
<tr>
<th>Index</th>
<th>Grade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fractal Dimension</td>
<td>Level I</td>
</tr>
<tr>
<td></td>
<td>$\leq X_{\alpha_1(n)}$</td>
</tr>
</tbody>
</table>

5. Back-Propagation Network (BPN)

An Artificial Neural Network (ANN) is a simplified simulation of biological neural networks in human brains. ANN is capable of “learning”; that is, it can be trained to improve its performance by either supervised or unsupervised learning. The back-propagation network (BPN) and the supervised learning, i.e., learned by samples, are chosen in this study. After learning (or training), the trained weight can be used for future prediction of debris flow occurrence. The BPN is an ANN using back-propagation algorithm and is one of the popular ANNs, which has been widely applied to many scientific and commercial fields for non-linear analysis and prediction. The structure of BPN contains three layers: input, hidden, and output layers as shown in Fig. 1. Each layer contains $I$, $J$, and $K$ nodes denoted respectively by circles. The node is also called neuron or unit. The circles are connected by links, denoted by arrows in Fig. 1, each of which represents a numerical weight. The $w_{ij}$ is denoted as numerical weights between input and hidden layers and so is $w_{jk}$ between hidden and output layers as also shown in Fig. 1. The processing or the computation is performed in each node in the hidden and output layers. The back propagation learning algorithm is composed of two procedures: (a) feed-forward and (b) back-propagation weight training.

![Fig.1. Structure of back-propagation neural network](image-url)
5.1. Feed-forward

Assume that each input factor in the input layer is denoted by $x_i$, the $y_j$ and $z_k$ represent the output in the hidden layer and the output layer, respectively. And, the $y_j$ and $z_k$ can be expressed as follows:

$$y_j = f(X_j) = f(w_{oj} + \sum_{i=1}^{j} w_{ij}x_i))$$

and

$$z_k = f(Y_k) = f(w_{ok} + \sum_{j=1}^{k} w_{jk}y_j)$$

where the $w_{oj}$ and $w_{ok}$ are the bias weights for setting threshold values, $f$ is the activation function used in both hidden and output layers, and $X_j$ and $Y_k$ are the temporarily computing results before applying activation function $f$. In this study, a sigmoid function (or logistic function) is selected as the activation function. Therefore, the actual outputs $y_j$ and $z_k$ in hidden and output layers, respectively, can be also written as:

$$y_j = f(X_j) = \frac{1}{1+e^{-X_j}}$$

and

$$z_k = f(Y_k) = \frac{1}{1+e^{-Y_k}}$$

The activation function $f$ introduces the non-linear effect to the network and maps the result of computation to a domain $(0, 1)$. This sigmoid function is differentiable. The derivative of the sigmoid function in Eqs. $(5a, b)$ can be easily derived as:

$$f' = f(1-f)$$

5.2. Back-propagation weight training

The error function is defined as [4]:

$$E = \frac{1}{2} \sum_{k=1}^{K} e_k^2 = \frac{1}{2} \sum_{k=1}^{K} (t_k - z_k)^2$$

where $t_k$ is a predefined network output (or desired output or target value) and $e_k$ is the error in each output node. The goal is to minimize $E$ so that the weight in each link is accordingly adjusted and the final output can match the desired output. To get the weight adjustment, the gradient descent strategy is employed. In the link between hidden and output layers, computing the partial derivative of $E$ with respect to the weight $w_{jk}$ produces
\[
\frac{\partial E}{\partial w_{jk}} = \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial Y_k} \frac{\partial Y_k}{\partial w_{jk}} = -e_k \frac{\partial f(Y_k)}{\partial Y_k} y_j = -e_k f'(Y_k) y_j = -\delta_k y_j
\]

where
\[
\delta_k = e_k f'(Y_k) = (t_k - z_k) f'(Y_k)
\]

The weight adjustment in the link between hidden and output layers is computed by
\[
\Delta w_{jk} = \alpha \cdot y_j \cdot \delta_k
\]

where \(\alpha\) is the learning rate, a positive constant between 0 and 1. The new weight herein can be updated by the following
\[
w_{jk}(n+1) = w_{jk}(n) + \Delta w_{jk}(n)
\]

where \(n\) is the number of iteration.

Similarly, the error gradient in links between input and hidden layers can be obtained by taking the partial derivative with respect to \(w_{ij}\)
\[
\frac{\partial E}{\partial w_{ij}} = \left[ \sum_{k=1}^{K} \frac{\partial E}{\partial z_k} \frac{\partial z_k}{\partial Y_k} \frac{\partial Y_k}{\partial w_{jk}} \right] \cdot \frac{\partial y_j}{\partial x_i} \frac{\partial X_j}{\partial w_{ij}} = -\Delta_j x_i
\]

where the \(\Delta_j\) can be derived as follows:
\[
\Delta_j = f'(X_j) \sum_{k=1}^{K} \delta_k w_{jk}
\]

The new weight in the hidden-input links can be now corrected as:
\[
\Delta w_{ij} = \alpha \cdot x_i \cdot \Delta_j
\]

and
\[
w_{ij}(n+1) = w_{ij}(n) + \Delta w_{ij}(n)
\]

Training the BP-networks with many samples is sometimes a time-consuming task. The learning speed can be improved by introducing the momentum term \(\eta\) [5]. Usually, \(\eta\) falls in the range [0, 1]. For the iteration \(n\), the weight change \(\Delta w\) can be expressed as
\[
\Delta w(n+1) = \eta \cdot \Delta w(n) + \alpha \cdot \frac{\partial E}{\partial w(n)}
\]

The back-propagation learning algorithm used in artificial neural networks is shown in many textbooks [6, 7, 8, 9].
6. Case Study

6.1. Structure of BPN for evaluation of mining geological condition

Determining the numbers of input and output nodes in BPN is a crucial point for evaluation of mining geological condition. This study summarized ten factors for ANN input. The seven input units are (1) fault throw, (2) fault density, (3) fault intensity, (4) fracture fractal dimension, (5) coal thickness, (6) abnormalities of coal thickness, (7) coal structure, (8) coal dip, (9) change of floor elevation, (10) combination of rock.

The output layer consists of three neurons with three output results (1, 0, 0), (0, 1, 0) and (0, 0, 1). The output (1, 0, 0) means the grade I of mining geological condition, the output (0, 1, 0) denotes the grade II, and the output (0, 0, 1) is the grade III. The number of neurons, J, in the hidden layer can be determined according to the following rules [10]:

\[ J = \frac{I + K}{2} \]  

in which I and K are the number of neurons in the input layer and output layer, respectively. Accordingly, the number of neurons in hidden layer can be computed to be \((10+3)/2 = 6.5\). The actual number of neurons used in the hidden layer is 7 as rounded to the integer obtained from Eq. (15).

6.2. Training samples and results

Range values of three levels have got after optimal three-stage divided for Dongpo Mine (Table 2). A total of 15 records used for training were selected from Dongpo Mine (Table 3). This study utilized these records to feed into the ANN model for training. The learning rate and momentum term were 0.01 and 0.87, respectively. The stop criterion of error function was set to 0.001 and the maximum number of iteration was 2000. The initial weights were random numbers generated by the computer.

Table 2. Grade of main index of structure

<table>
<thead>
<tr>
<th>Index</th>
<th>Grade of structure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fault throw</td>
<td>Level I</td>
</tr>
<tr>
<td>Fault density</td>
<td>&lt;2</td>
</tr>
<tr>
<td>Fault intensity</td>
<td>&lt;6.46</td>
</tr>
<tr>
<td>Fracture fractal dimension</td>
<td>&lt;0.9</td>
</tr>
<tr>
<td>Coal thickness</td>
<td>&gt;2.5</td>
</tr>
<tr>
<td>Abnormalities of Coal thickness</td>
<td>&lt;0.64</td>
</tr>
<tr>
<td>Coal structure</td>
<td>1</td>
</tr>
<tr>
<td>Coal dip</td>
<td>&lt;15°</td>
</tr>
<tr>
<td>Change of floor elevation</td>
<td>&lt;6.2</td>
</tr>
<tr>
<td>Combination of rock</td>
<td>4</td>
</tr>
</tbody>
</table>
After 1769 times trained, a single study sample error of less than 5%, which shows convergence of network, results of training samples show as Table 3.

Table 3. Trained samples and results of evaluation

<table>
<thead>
<tr>
<th>Samples no.</th>
<th>Desired output</th>
<th>Actual output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1 0 0</td>
<td>0.961 0.042 0.006</td>
</tr>
<tr>
<td>2</td>
<td>1 0 0</td>
<td>0.960 0.041 0.006</td>
</tr>
<tr>
<td>3</td>
<td>1 0 0</td>
<td>0.960 0.041 0.006</td>
</tr>
<tr>
<td>4</td>
<td>1 0 0</td>
<td>0.960 0.041 0.006</td>
</tr>
<tr>
<td>5</td>
<td>1 0 0</td>
<td>0.948 0.047 0.007</td>
</tr>
<tr>
<td>6</td>
<td>0 1 0</td>
<td>0.049 0.951 0.039</td>
</tr>
<tr>
<td>7</td>
<td>0 1 0</td>
<td>0.042 0.952 0.041</td>
</tr>
<tr>
<td>8</td>
<td>0 1 0</td>
<td>0.042 0.952 0.041</td>
</tr>
<tr>
<td>9</td>
<td>0 1 0</td>
<td>0.042 0.952 0.041</td>
</tr>
<tr>
<td>10</td>
<td>0 1 0</td>
<td>0.041 0.955 0.047</td>
</tr>
<tr>
<td>11</td>
<td>0 0 1</td>
<td>0.013 0.047 0.959</td>
</tr>
<tr>
<td>12</td>
<td>0 0 1</td>
<td>0.012 0.045 0.955</td>
</tr>
<tr>
<td>13</td>
<td>0 0 1</td>
<td>0.012 0.045 0.955</td>
</tr>
<tr>
<td>14</td>
<td>0 0 1</td>
<td>0.012 0.045 0.955</td>
</tr>
<tr>
<td>15</td>
<td>0 0 1</td>
<td>0.012 0.045 0.955</td>
</tr>
</tbody>
</table>

Dongpo Mine is divided into 27 units by 500×500m network, respectively, the data of evaluation index are collected. Using the trained network to predict 27 unknown units, the results of the evaluation are archived. At the same time, fuzzy comprehensive evaluation analysis is also carried out for each unit. Two results of evaluation are shown in Table 4. These outcomes demonstrate that the Ten-factor-ANN model is stable and reliable for coal-mining geological condition training and evaluation.

Table 4. Comparison with BPN and fuzzy comprehensive evaluation analysis

<table>
<thead>
<tr>
<th>Units No.</th>
<th>results of fuzzy comprehensive evaluation analysis</th>
<th>results of BPN</th>
<th>Units No.</th>
<th>results of fuzzy comprehensive evaluation analysis</th>
<th>results of BPN</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>I</td>
<td>I</td>
<td>15</td>
<td>II</td>
<td>II</td>
</tr>
<tr>
<td>2</td>
<td>III</td>
<td>III</td>
<td>16</td>
<td>II</td>
<td>II</td>
</tr>
<tr>
<td>3</td>
<td>II</td>
<td>II</td>
<td>17</td>
<td>II</td>
<td>II</td>
</tr>
<tr>
<td>4</td>
<td>II</td>
<td>II</td>
<td>18</td>
<td>I</td>
<td>I</td>
</tr>
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<td>II</td>
<td>II</td>
<td>19</td>
<td>I</td>
<td>I</td>
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<tr>
<td>6</td>
<td>I</td>
<td>I</td>
<td>20</td>
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<td>12</td>
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<td>13</td>
<td>II</td>
<td>II</td>
<td>27</td>
<td>I</td>
<td>I</td>
</tr>
<tr>
<td>14</td>
<td>II</td>
<td>III</td>
<td></td>
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</tbody>
</table>
7. Conclusions

This study presents a simple and easy ANN model using back-propagation learning algorithm for evaluation and prediction of mining geological condition. In order to get a stable and reliable prediction, seven significant factors of debris flows were chosen for ANN input and analysis. These seven factors are: (1) fault throw, (2) fault density, (3) fault intensity, (4) fracture fractal dimension, (5) coal thickness, (6) abnormalities of coal thickness, (7) coal structure, (8) coal dip, (9) change of floor elevation, (10) combination of rock.

In a guarding system, this analytical model can be used to predict the current condition, while other conditions to be predicted by changing some factors or input data. Still, further research is required for improving the accuracy of prediction. For example, the critical value and the influence percentage of each factor need more investigation and research. Also, the degree of risk assessment of mining geological condition has to be done with more work.

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References