Optimization for blasting scheme of crown-sill pillar based on CW-GT and GC-WTOPSIS

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Blasting scheme for crown-sill pillar of a lead–zinc mine was optimized by a new combination optimization model on the basis of CW-GT and GC-WTOPSIS. Nine main evaluation indices influencing blasting were chosen from economy, technology and safety aspects to establish the synthetic evaluation index system of four blasting schemes. Then the synthetic superiority degrees of the four schemes were determined with the basic theory of CW-GT and GC-WTOPSIS. Scheme-III (burn cut, inclined hole and side collapse with an angle of 80°) had the highest superiority degree and hence was confirmed as the best. The result was consistent with AHP-TOPSIS, BP neural network and catastrophe progressing model. The practice showed that the selected blasting scheme achieved the desired blasting effect, and the new method was suitable for optimization of blasting scheme, which provided a new way for scientific and reliable optimization of similar programmes.

Keywords: Blasting scheme, combination weight based on game theory, CW-GT, GC-WTOPSIS.

SELECTING the blasting scheme for crown-sill pillar is a multi-objective, multi-level, multi-factor and complex decision problem[1]. In other words, the selection process is impacted by many random, fuzzy and uncertain factors, and the selected blasting scheme decides the blasting effect. However, in the previous decision-making process, the optimal blasting scheme mostly relied on the experience of experts to judge. Generally, since there is strong subjectivity, it is difficult to obtain the optimal blasting scheme in traditional ways[2,3].

Many theories including the fuzzy analytic hierarchy process method[4], osculating value method[2], gray correlation analysis[5], catastrophe theory[6], accelerating genetic algorithm[7] and neural network theory[8] were used in several studies to select and optimize the blasting scheme. Although the application of these methods has achieved some results, there still exists limitations. For example, the fuzzy analytic hierarchy process, traditional gray correlation analysis and accelerating genetic algorithm had certain degree of subjectivity and uncertainty when calculating the weight of influence factors. The gray correlation analysis did not take into account the relative significant degree of various factors. Moreover, the neural network theory needed a large number of sample data. It is hard to set parameters and easy to fall into local minimum value with slow convergence[9–11].

In addition, the game theory, combination weight, gray correlation analysis theory and TOPSIS method have rarely been reported in the optimization of blasting schemes. Therefore, a new combination optimization model – combination weight based on game theory and weighted TOPSIS improved by gray correlation (CW-GT and GC-WTOPSIS) based on results from previous studies was proposed. It was used to optimize the mining blasting scheme of crown-sill pillar and to verify the feasibility of optimization for the blasting scheme.

In the practical multi-objective decision-making case, if a single weighting method, a one-sided way, is used, it could bring some subjectivity or could ignore the degree of importance of different indices in the decision-making process[12]. Besides, the general combination forms of the subjective weight and objective weight are impacted by certain subjectivity factors[13]. Therefore, to obtain a more accurate and reliable comprehensive weight, based on analytic hierarchy process (AHP)[14–16] and entropy weight[17,18], the CW-GT is built using game theory.

AHP is considered as a subjective weighting method. AHP, as a multi-objective decision method, considers sufficiently the accumulated practical experiences of experts. AHP combines corresponding comparative standards and calculation methods to determine the subjective weight of each assessment index according to expert judgment. In accordance with the AHP principle, the higher the weight, the better the role of evaluation index for influence decision. It has also been used to solve many decision problems in both engineering practice and academic research[19]. In view of this, this paper does not repeat the calculation steps, but quotes indices weight by ref. 1.

The objective weight based on entropy method[20–22] is given as

$$E_j = -\frac{1}{\ln m}\left(\sum_{i=1}^{m} v_{ij} \ln v_{ij}\right),\ (i, j = 1, 2, 3, \ldots), \tag{1}$$

where $v_{ij} = r_{ij} / \sum_{i=1}^{m} r_{ij}$, and if $v_{ij} = 0$, then $v_{ij} \ln v_{ij} = 0$

$$z_j = \frac{1-E_j}{n-\sum_{j=1}^{n} E_j},\ \text{and}\ \sum_{j=1}^{n} z_j = 1, \tag{2}$$

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where m is the number of schemes; v_{ij} the average value of the index. E_j the information entropy and $0 \le E_j \le 1$; n the number of indices and z_i is the entropy weight of the jth index.

Since combination weighting combines subjective weight vector w and objective weight vector z, the goal of optimal combination weight h_f is achieved. To derive h_f, four formulas must be implemented[13].

In allusion to a multi-objective decision problem, there are w kinds of different weighting methods. The different weight vectors are calculated respectively, that is $\{h_1, h_2, \ldots, h_k\}$, where $k = 1, 2, \ldots, s$. Then, the $(s = 2)$ kinds of different weight vectors are arbitrary linear combined by

$$h = \sum_{k=1}^{s} \beta_k h_k^T, \tag{3}$$

$$\min = \left\| \sum_{k=1}^{s} \beta_k h_k^T - h_k^T \right\|, \tag{4}$$

where β_k denotes the combination coefficient among the vectors, h_k denotes the weight vector, h_k^T is the transpose matrix of h_k and h denotes combination weight vector. According to game theory, if we are to obtain the optimal combination weight h_f that is the ideal solution of h, we should optimize combination coefficient β_k. We can obtain the deviation minimization formulation model between h and h_k.

Considering the differential properties of the matrix, the optimization first derivative of eq. (4) is obtained, as eq. (5) shown below. We can then build the corresponding linear equations as shown in eq. (6)

$$\sum_{k=1}^{s} \beta_k h_k h_k^T = h_k h_k^T, \tag{5}$$

$$\begin{vmatrix} h_1 \cdot h_1^T & \cdots & h_1 \cdot h_s^T \\ \vdots & \ddots & \vdots \\ h_s \cdot h_1^T & \cdots & h_s \cdot h_s^T \end{vmatrix} \cdot \begin{vmatrix} \beta_1 \\ \vdots \\ \beta_s \end{vmatrix} = \begin{vmatrix} h_1 \cdot h_1^T \\ \vdots \\ h_s \cdot h_s^T \end{vmatrix}. \tag{6}$$

Combination coefficient vector $(\beta_1, \beta_2, \ldots, \beta_s)$ is derived by eq. (6). After the normalization processing, the result is introduced into eq. (3) to get the optimal combination weight h_f.

GC-WTOPSIS is an improved optimization method. The schemes are ranked by determining the relative closeness between schemes and the positive ideal solution according to this method. The combination weight and gray correlation coefficient are introduced into the traditional TOPSIS through corresponding ways, overcoming the disadvantages that the TOPSIS ignore the curve trend, and reflecting the trend relationship between a scheme and the positive ideal solution, and the actual situation of problems. Thus, the formulae of GC-WTOPSIS[23–25].

There are two types of indices in matrix R. One is positive and the larger it is the better. The other is negative and the smaller it is the better. So different types of indices must be normalized by eqs (7) and (8) to eliminate the influence of different dimensions of indices

$$d_{ij} = \begin{cases} 1 & r_{ij} = \max r_{ij} \\ \dfrac{r_{ij}}{\max r_{ij}} & r_{ij} < \max r_{ij} \end{cases} \quad \text{positive index,} \tag{7}$$

$$d_{ij} = \begin{cases} 1 & r_{ij} = \min r_{ij} \\ \dfrac{\min r_{ij}}{r_{ij}} & r_{ij} > \min r_{ij} \end{cases} \quad \text{negative index,} \tag{8}$$

where d_{ij} is the normalized value of the jth index of the ith scheme; r_{ij} the evaluation value of the jth index of the ith scheme; $\min r_{ij}$ and $\max r_{ij}$ are the minimum and maximum indices values in the scheme $(i, j = 1, 2, \ldots)$.

Weighting the decision matrix R and calculating the gray correlation coefficient: Combination weight h_f consisting of subjective weight w and objective weight z is obtained and it is weighted into decision making matrix R, getting the normalized weighted matrix $Q = (q_{ij})_{i\times j} = (h_f \times d_{ij})_{i\times j}$

$$Q_{(i\times j)} = \begin{vmatrix} h_1 d_{11} & h_2 d_{12} & \cdots & h_f d_{1j} \\ h_1 d_{21} & h_2 d_{22} & \cdots & h_f d_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ h_1 d_{i1} & h_2 d_{i2} & \cdots & h_f d_{ij} \end{vmatrix}, \tag{9}$$

$$\varphi_i(j) = \frac{\min\limits_i \min\limits_j \left|q_{0j} - q_{ij}\right| + \rho \max\limits_i \max\limits_j \left|q_{0j} - q_{ij}\right|}{\left|q_{0j} - q_{ij}\right| + \rho \max\limits_i \max\limits_j \left|q_{0j} - q_{ij}\right|}, \tag{10}$$

where q_{ij} denotes the jth index of the ith scheme in the normalized weighted matrix Q. The optimal indices are selected from the weighted matrix $Q_{(i\times j)}$ to compose the optimal scheme Q_0^x $(x = 1, 2, 3, \ldots)$, i.e. $Q_0^x = \{q_{0j} | j = 1, 2, \ldots, n\}$, q_{0j} is the most ideal value of the jth index in matrix Q_0^x and Q_0^x is the set of q_{0j}. $\varphi_i(j)$, i.e. φ_{ij}, is the gray correlation coefficient of the jth index between the ith scheme and the optimal scheme.

$\min\limits_i \min\limits_j |q_{0j} - q_{ij}|$ and $\max\limits_i \max\limits_j |q_{0j} - q_{ij}|$ are respectively the minimum and maximum difference. ρ is the resolution coefficient weakening the distortion effects; $\rho \in (0, 1)$, usually, $\rho = 0.5$.

Building the gray correlation coefficient matrix and composing the positive ideal solution and negative ideal solution affected by index normalization

$$\varphi_{(i\times j)} = \begin{vmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1j} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{i1} & \varphi_{i2} & \cdots & \varphi_{ij} \end{vmatrix}, \quad (11)$$

$$T^+ = \{(\max \varphi_{ij} \mid j \in L_1), (\min \varphi_{ij} \mid j \in L_2)\}, \quad (12)$$

$$T^- = \{(\min \varphi_{ij} \mid j \in L_1), (\max \varphi_{ij} \mid j \in L_2)\}, \quad (13)$$

where $\varphi_{(i\times j)}$ is the gray correlation coefficient matrix. T^+ and T^- are respectively the positive and negative ideal solution affected by normalization. L_1 and L_2 are respectively the positive index and negative index sets. j denotes the jth index of the index set.

Calculating the relative closeness X_i^+ between the positive ideal solution and the schemes is based on the distance of scheme from the positive and negative ideal solution

$$D_i^+ = \sqrt{\sum_{j=1}^{n} (\varphi_{ij} - \varphi_j^+)^2}, \quad D_i^- = \sqrt{\sum_{j=1}^{n} (\varphi_{ij} - \varphi_j^-)^2}, \quad (14)$$

$$X_i^+ = \frac{D_i^-}{D_i^- + D_i^+}, \quad (15)$$

where D_i^+, D_i^- are respectively the distances of the schemes from the positive and negative ideal solution. φ_j^+, φ_j^- are the corresponding elements in the positive and negative ideal solution. X_i^+ satisfies $0 \le X_i^+ \le 1$, which means that if the relative closeness X_i^+ is closer to 0, the scheme is more closer to the negative ideal solution; conversely, the scheme is more close to the positive ideal solution. When the X_i^+ is in descending order from 0 to 1, schemes can be preliminary selected by comparing the value of X_i^+.

Comprehensive evaluation of schemes.

$$P = I^* \times X, \quad (16)$$

where P denotes the result vector of synthetic superiority degree of each scheme, I^* the weight vector of the criterion layer and X is the relative closeness evaluation matrix established by the evaluation schemes and positive ideal solution.

This new model was verified by a case from the blasting scheme for the crown-sill pillar of a lead–zinc mine[1]. After decades of mining, there are large numbers of high grade lead–zinc crown-sill pillars at about 70° of dip angle in the mine, that is one of the biggest lead–zinc mines in China. There are higher galena and sphalerite contents and better drillability, and blastability, due to the limitations of the early mining methods (large-diameter long-hole). Because the relative difficult conditions for the construction of drilling holes and the ventilation of drill drift had existed, as well as the weak orebody and surrounding rock. For the safety consideration, the size of the mining drilling chamber constructed is small. Therefore, to determine the blasting scheme and to evaluate its characteristics of crown-sill pillar under this circumstance is tough.

Considering the factors influencing blasting and the local conditions of the project, nine main indices from economy, technology and safety aspects were chosen. The synthetic evaluation index system is established in Table 1. Parameters considered in the system could be adjusted properly based on actual situation. Note: The indices belonging to the layer C_1 were determined according to the standard cost of mining industry. The others, from layers C_2 and C_3, were generated by expert opinions, taking a full account of the opinions of the authoritative experts and technicians to quantify indices based on expert scoring method with a scoring range of [0, 1].

Four blasting schemes, Figures 1–4, were put forward by engineering technicians and experts as: scheme-I: burn cut, straight hole and side collapse; scheme-II: burn cut, inclined hole and side collapse with an angle of 85°; scheme-III: burn cut, inclined hole and side collapse with an angle of 80°; scheme-IV: inclined-hole cut, inclined hole and side collapse with an angle of 80°. The spacing of the cut hole is 1.0 m, and the spacing of side collapse hole is 1.3 m. Moreover, the simplified schematic diagram of stope operation is shown in Figure 5. The thickness of the crown pillar is the same as the height of the stope, i.e. y. The length and width of the stope are respectively b, d, y = 6.0 m, b = 11.0 m, d = 4.5 m.

Subjective weight was determined by directly quoting the weight given by AHP from the ref. (1), that is the weight vector I^* and w_i.

With the AHP principle, the judgment matrix P–C between the project layer and criterion layer was constructed by referencing numerous engineering examples and discussing the importance of variation of indices as well as their quantification with on-site experts and technicians.

The consistency ratio of the matrix P–C was $0.0017 < 0.1$, satisfying the consistency[1]. Similarly, we could get the weight of each index involved in C_1-I, C_2-I and C_3-I layer

$$P - C = \begin{vmatrix} P-C & C_1 & C_2 & C_3 & \text{weight}(I^*) \\ C_1 & 1 & 1/4 & 1/2 & 0.143 \\ C_2 & 4 & 1 & 2 & 0.571 \\ C_3 & 2 & 1/2 & 1 & 0.286 \end{vmatrix}.$$

For calculating objective weight z_j eqs (1) and (2) were used.

Combination coefficient vector β_k and combination weight h_f were determined by using eqs. (3)–(6), i.e. $w{\cdot}w^T = 0.2034$, $w{\cdot}z^T = 0.1029$ and $z{\cdot}z^T = 0.4008$. Consequently, the normalized combination coefficient vector was determined as: $(\beta_1, \beta_2) = (0.3993, 0.6007)$.

$$\left|\begin{array}{lllll} C-I & I_1 & I_2 & I_3 & I_4 \\ w(C_1) & 0.143 & 0.190 & 0.762 & 0.048 \\ w(C_2) & 0.571 & & & 0.226 \\ w(C_3) & 0.286 & & & \\ \text{weight } (w_i) & 0.027 & 0.109 & 0.007 & 0.129 \end{array}\right.$$

$$\times \left.\begin{array}{llllll} C-I & I_5 & I_6 & I_7 & I_8 & I_9 \\ w(C_1) & 0.143 & & & & \\ w(C_2) & 0.571 & 0.135 & 0.639 & & \\ w(C_3) & 0.286 & & 0.571 & 0.286 & 0.143 \\ \text{weight } (w_i) & 0.077 & 0.365 & 0.163 & 0.082 & 0.041 \end{array}\right|$$

$$\left|\begin{array}{lllll} \bar{r}_{ij} & 46.250 & 1.800 & 2.150 & 0.883 \\ -\sum_{i=1}^{m} v_{ij} \ln v_{ij} & 1.3808 & 1.3486 & 1.3783 & 1.3844 \\ E_j & 0.9960 & 0.9728 & 0.9942 & 0.9986 \\ \text{weight } (z_j) & 0.089 & 0.607 & 0.130 & 0.031 \end{array}\right.$$

$$\times \left.\begin{array}{llllll} \bar{r}_{ij} & 0.908 & 0.813 & 0.783 & 0.745 & 0.825 \\ -\sum_{i=1}^{m} v_{ij} \ln v_{ij} & 1.3855 & 1.322 & 1.3860 & 1.3851 & 1.3839 \\ E_j & 0.9994 & 0.9970 & 0.9998 & 0.9991 & 0.9983 \\ \text{weight } (z_j) & 0.013 & 0.067 & 0.005 & 0.020 & 0.038 \end{array}\right|$$

$$\left|\begin{array}{lllll} h_f = \beta_1 \cdot w_i + \beta_2 \cdot z_j & h_1 & h_2 & h_3 & h_4 \\ \text{weight } (h_f) & 0.064 & 0.408 & 0.081 & 0.070 \end{array}\right.$$

$$\left.\begin{array}{llllll} h_f = \beta_1 \cdot w_i + \beta_2 \cdot z_j & h_5 & h_6 & h_7 & h_8 & h_9 \\ \text{weight } (h_f) & 0.039 & 0.186 & 0.068 & 0.045 & 0.039 \end{array}\right|.$$

Calculation of GC-WTOPSIS: Evaluation indices in Table 1 were normalized according to eqs (7) and (8). Then, the weighted normalization matrix Q_E^T of economy indices, and similarly Q_T^T, Q_S^T, was derived by eq. (9)

$$Q_E^T = \begin{vmatrix} 0.064 & 0.408 & 0.073 \\ 0.058 & 0.326 & 0.058 \\ 0.053 & 0.245 & 0.063 \\ 0.048 & 0.196 & 0.081 \end{vmatrix}.$$

Evaluating economy indices: The weighted normalization matrix of the economy layer was obtained from the matrix Q^T. We then selected the optimal indices from the weighted normalization matrix of the economy layer to establish the optimal scheme Q_0^1, i.e. $Q_0^1 = [0.064, 0.408, 0.081]$. The eqs (10) and (11) were used to calculate the gray correlation coefficient matrix φ_1.

$$\varphi_1 = \begin{vmatrix} 0.869 & 0.333 & 0.876 \\ 0.914 & 0.449 & 1 \\ 0.955 & 0.684 & 0.955 \\ 1 & 1 & 0.822 \end{vmatrix}.$$

The gray correlation positive ideal solution T_1^+ and corresponding negative ideal solution T_1^- of economy indices were given by eqs (12) and (13)

$$\begin{cases} T_1^+ = [0.869, \ 0.333, \ 0.822] \\ T_1^- = [1.000, \ 1.000, \ 1.000]. \end{cases}$$

The distance D_i^+, D_i^- of the schemes from the positive and negative ideal solution were determined from eq. (14)

$$\begin{cases} D_1^+ = [0.054, \ 0.217, \ 0.385, \ 0.680] \\ D_1^- = [0.691, \ 0.390, \ 0.322, \ 0.178]. \end{cases}$$

The relative closeness X_1^+ between schemes and positive ideal solution was calculated using eq. (15)

$$X_1^+ = [0.928, \ 0.643, \ 0.455, \ 0.207].$$

Evaluating technology and safety indices: Likewise, the relative closeness X_2^+ and X_3^+ was obtained, illustrated in Figure 6

$$X_2^+ = [0.366, \ 0.337, \ 0.762, \ 0.401],$$
$$X_3^+ = [0.554, \ 0.724, \ 0.652, \ 0.446].$$

The comparison results are as follows: Under the E-layer (economy layer), the best scheme is scheme-I. The economic effects of straight hole form is better than other hole forms in the blasting operation, agreeing well with

Table 1. Synthetic evaluation index system of schemes[1]

Project (P)					
Criterion layer	Index layer	Scheme-I	Scheme-II	Scheme-III	Scheme-IV
Economic layer C_1	Construction cost I_1 (yuan RMB·m^{-1})	40	44	48	53
	Management cost I_2 (yuan RMB·t^{-1})	1.2	1.5	2.0	2.5
	Blasting cost I_3 (yuan RMB·t^{-1})	2.0	2.5	2.3	1.8
Technical layer C_2	Degree of difficulty in operation I_4	0.95	0.90	0.88	0.80
	Adaptive degree of scheme I_5	0.95	0.93	0.90	0.85
	The blasting effect of experts' experience I_6	0.70	0.80	0.90	0.85
Safety layer C_3	Ventilation condition I_7	0.80	0.80	0.78	0.75
	Influence degree of the operation for workers I_8	0.70	0.73	0.75	0.80
	Influence degree of blasting for surrounding environment I_9	0.90	0.85	0.80	0.75

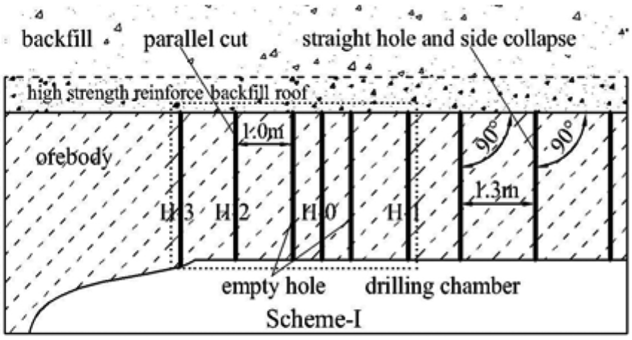

Figure 1. Diagram of blasting scheme-I.

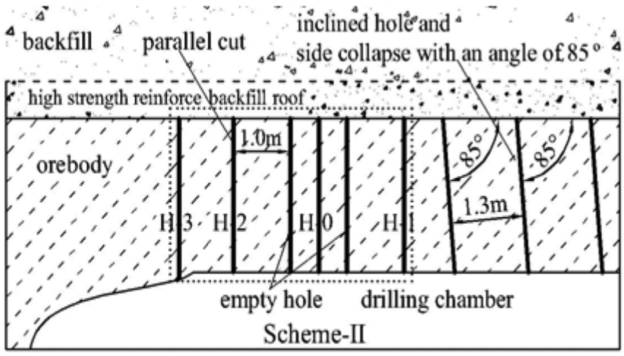

Figure 2. Diagram of blasting scheme-II.

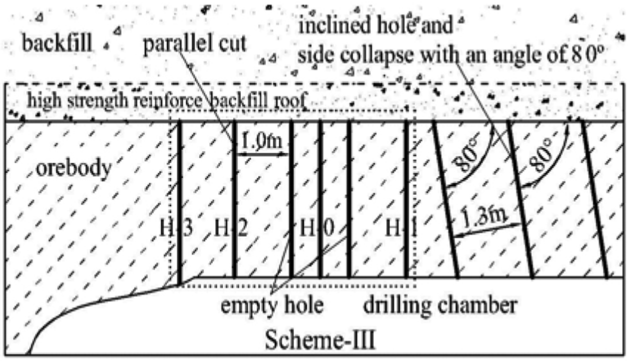

Figure 3. Diagram of blasting scheme-III.

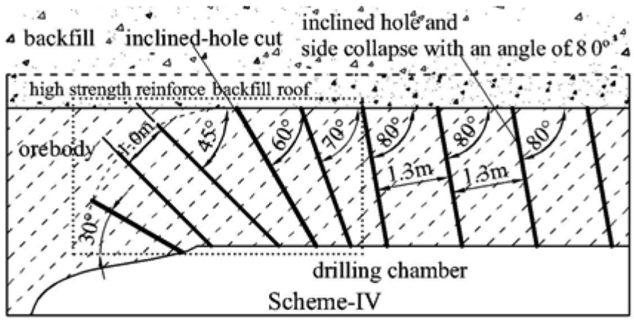

Figure 4. Diagram of blasting scheme-IV.

the actual situation. Under the T-layer (technology layer), the best scheme is scheme-III. The goal to achieve the best blasting operation of the mining crown-sill pillar which is coincident to the desired target and experts' engineering experiences significantly requires better adaptability and effects of the selected blasting scheme than others. Under the S-layer (safety layer), the best scheme is scheme-II, reflecting the safety first principle, that constructing gently inclined and straight hole are more safe and simple than inclined hole. It is significant for constructors to keep a safe construction environment of stope. In summary, scheme advantages under different layers given by the new model conform well with actuality.

Comprehensive ranking of blasting schemes: Constructing the evaluation matrix X of relative closeness of schemes, combined with the weight vector I^* of the criterion layer, the value of vector P in eq. (16) could be derived by the principle of maximum membership. The greater the value of vector P, the more likely is the selection of the corresponding scheme.

$$X = \begin{vmatrix} 0.928 & 0.643 & 0.455 & 0.207 \\ 0.366 & 0.337 & 0.762 & 0.401 \\ 0.554 & 0.724 & 0.652 & 0.446 \end{vmatrix}$$

$$P = I^* \times X = (0.500, \quad 0.491, \quad 0.687, \quad 0.386).$$

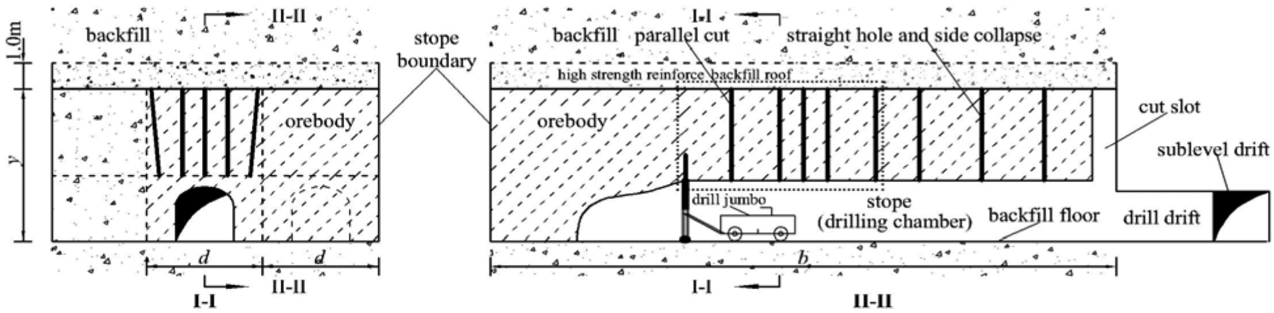

Figure 5. Simplified schematic diagram of stope operation.

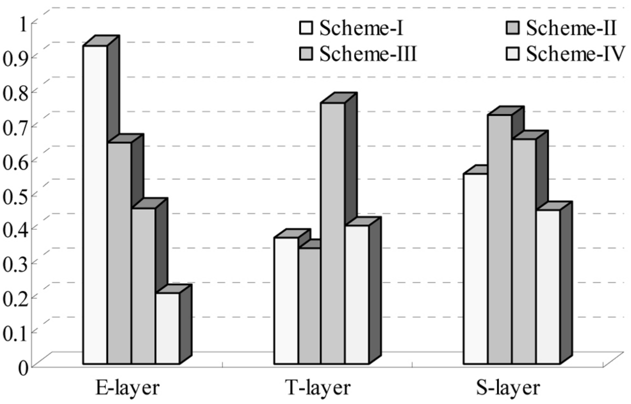

Figure 6. Relative closeness from three layer of schemes.

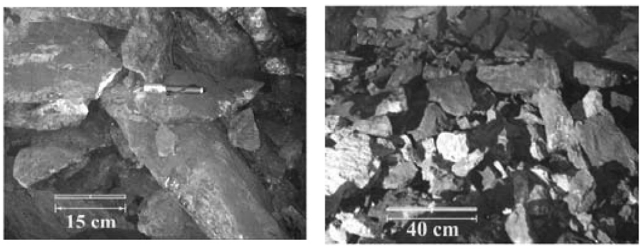

Figure 7. Ore fragment photos of the lead–zinc mine.

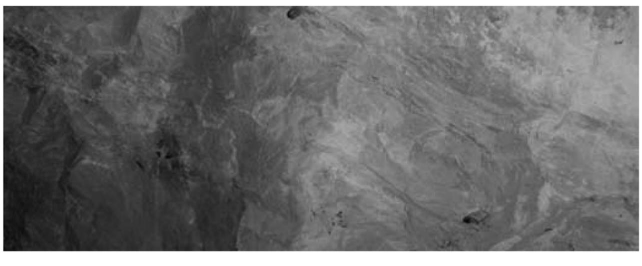

Figure 8. The stope roof photo after blasting.

As seen, the synthetic superiority degrees of the four blasting schemes are obtained as follows: scheme-I: 50.0%, scheme-II: 49.1%, scheme-III: 68.7%, scheme-IV: 38.6%. Hence the synthetic superiority degrees of schemes were ordered as III > I > II > IV. The best scheme was scheme-III (burn cut, inclined hole and side collapse with an angle of 80°) and was superior to other schemes. It is clear that the optimal blasting scheme determined by the new model is the same as the optimal scheme in the ref. (1).

The rankings of blasting schemes were basically consistent with the rankings derived by the AHP-TOPSIS, catastrophe progressing and BP neural network model. The differences in ranking were due to the introduction of objective weights, game theory and weighted TOPSIS improved by gray correlation, which remedied the shortcomings of each component and revealed that the changes in indices values in schemes had great nonlinear effect on the selection result of the scheme during actual blasting scheme selection. Because the correlation degrees between different schemes were derived from the relevance relationship quantitated between each index value of different schemes.

Field tests showed that the selected blasting scheme was economically feasible and operationally simple. The desired blasting effects including the smooth blasting cut, less damage to the roof of the filling body without large roof caving, and the uniform ore fragment beneficial to the extraction were also achieved. Photos of the lead–zinc ore fragment and the stope roof are shown in Figure 7 *a* and *b* and Figure 8 respectively.

By constructing, CW-GT and GC-WTOPSIS, the new combination optimization model and choosing nine main indices affecting blasting schemes from economy, technology and safety aspects, the synthetic evaluation index system was built to optimize mining blasting scheme for the crown-sill pillar of a lead–zinc mine. The synthetic superiority degrees of four schemes were determined through the new model. Scheme-III was confirmed the best, which was consistent with the result of AHP-TOPSIS, indicating its feasibility for optimal selection of the blasting scheme.

The CW-GT exploited complete information of indices, and the improved GC-WTOPSIS was beneficial in enhancing the application of weight and made up the drawbacks that did not reflect nonlinear relationship between the changes of indices and the superiority degrees of scheme themselves applying the convention theories in actual situation. And as the schemes at different criterion layers all have inherent advantages. Both of above points offered good theoretical basis for directly judging schemes.

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