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MULTI-OBJECTIVE OPTIMIZATION OF STOPE STRUCTURE PARAMETERS IN BROKEN ROCK CONDITIONS USING GREY RELATIONAL ANALYSIS

WIELO-KRYTERIALNA OPTYMALIZACJA PARAMETRÓW STRUKTURY PRZODKA WYBIERKOWEGO W WARUNKACH PĘKANIA SKAŁ PRZY WYKORZYSTANIU 'SZAREJ' ANALIZY RELACYJNEJ

In order to optimize the stope structure parameters in broken rock conditions, a novel method for the optimization of stope structure parameters is described. The method is based on the field investigation, laboratory tests and numerical simulation. The grey relational analysis (GRA) is applied to the optimization of the stope structure parameters in broken rock conditions with multiple performance characteristics. The influencing factors include stope height, pillar diameter, pillar spacing and pillar array pitch, the performance characteristics include maximum tensile strength, maximum compressive strength and ore recovery rate. The setting of influencing factors is accomplished using the four factors four levels Taguchi experiment design method, and 16 experiments are done by numerical simulation. Analysis of the grey relational grade indicates the first effect value of 0.219 is the pillar array pitch. In addition, the optimal stope structure parameters are as follows: the height of the stope is 3.5 m, the pillar diameter is 3.5 m, the pillar spacing is 3 m and the pillar array pitch is 5 m. In-situ measurement shows that all of the pillars can basically remain stable, ore recovery rate can be ensured to be more than 82%. This study indicates that the GRA method can efficiently applied to the optimization of stope structure parameters.

Keywords: Grey relational analysis; stope structure parameters; in broken rock conditions; numerical simulation; taguchi experiment design

W pracy zaproponowano nową metodę optymalizacji parametrów struktury przodka wybierkowego prowadzonego w warunkach pękania skał. Metoda opiera się na badaniach terenowych, wykorzystuje także badania laboratoryjne oraz symulacje numeryczne. Do optymalizacji parametrów struktury przodka wybierkowego prowadzonego w warunkach pękania skał dla wielu wariantów charakterystyki górotworu wykorzystano 'szarą' analizę relacyjną (GRA – Grey Relational Analysis). Uwzględnione czynniki wpływu to wysokość przodka, średnica filarów, rozstaw filarów, rozmieszczenie filarów oraz

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charakterystyki górotworu: maksymalna wytrzymałość na rozciąganie oraz ściskanie oraz uzysk rudy. Ustawienia czynników wpływu dokonano z wykorzystaniem czterech czynników i dla czterech poziomów wg metody Taguchi planowania eksperymentów; ponadto 16 eksperymentów wykonano z wykorzystaniem symulacji numerycznych. Wyniki 'szarej' analiza relacyjnej wskazują, że wartość efektywna dla pierwszego z czynników, czyli rozmieszczenia filarów, wyniosła 0.219. Ponadto, otrzymano następujące optymalne parametry przodka: wysokość przodka 3.5 m; średnica filarów 3.5 m, rozstęp pomiędzy filarami 3 m, rozciągłość filarów 5 m. Pomiary przeprowadzone in situ wykazały, że wszystkie filary zasadniczo powinny zachować stabilność, a uzysk rudy przekroczyć może 82%. Wyniki wskazują, że 'szara' analiza relacyjna może być z powodzeniem wykorzystywana do optymalizacji parametrów struktury przodka wybierkowego.

Słowa kluczowe: 'szara' analiza relacyjna, parametry struktury przodka wybierkowego, pękanie skał, symulacje numeryczne, model Taguchi projektowania eksperymentu

1. Introduction

The availability of adequate supply of mineral resources is the requirement for the commencement of a mining operation (Luo et al., 2012). In the process of mining, there may exits many problems affecting the safety mining and ore recovery rate. Stope structure parameters are one of the most important factors affecting the safety and efficiency mining. It is necessary to adopt different stope structure parameters according to different complex geological conditions (Song et al., 2011). There are many factors when selecting the stope structure parameters, it is mainly determined by the occurrence conditions, construction factors, exposure time, occurrence of rock masses, geological conditions, stability of rock mass, etc. (Chen et al., 2017). If the diameter is too large, the pillar spacing and pillar array pitch are too small, then the ore recovery rate will be low (Bagde et al., 2017), on the contrary, the stability of the pillar decreases, the probability of ground pressure activity increases, which is a big threat to the safety production (Shnorhokian et al., 2015). Therefore, it is necessary to optimize stope structure parameters, so as to ensure the safety and efficiency mining (Qin et al., 2010).

At present, many studies about the stope structure parameter optimization were done at home and abroad (Bai et al., 2013). Zhou Keping adopted the theoretical method Mathew and numerical simulation to optimize stope structure parameters, and analyzed the stability of the stope (Zhou et al., 2013). A three dimensional numerical simulation model was established by Guo, the failure mechanism of pillar was discussed, and the main failure modes of the pillar included compression failure and tensile failure (Yao et al., 2014). Cheng Jian proposed the AHP and TOPSIS method to study the optimal stope structure parameters, also the result was applied to the field, it indicated that the effect was good (Cheng et al., 2014). Zhang Julian suggested that combined with the laboratory tests and chaos theory, the effect of influencing factors can be reflected by the model, it shows that there are several parameters affecting the performance of stope structure parameters on room and pillar method in broken rock conditions, which include stope height, pillar diameter, pillar spacing , pillar array pitch, etc. (Zhang et al., 2005). Also Peng Kang established the response surface model to optimize the parameters, although the stope structure parameters were obtained in the sea mining, only the stability of the pillar was considered, and the ore recovery was ignored (Kang et al., 2011).

To sum up, many investigations have been done to improve the efficiency of optimization stope structure parameters. Be different from previous works (Sameera et al., 2015), grey relational analysis was applied to the optimization of stope structure parameters in broken rock conditions in this paper, for it has been applied for many domains of optimization, such as energy (Wang et al., 2015), electrical (Tripathy et al., 2016), metallurgical (Kao et al., 2003), and mining (Wang et al., 2016). Moreover, the grey relational analysis method utilizes the mathematical method to analyze correlations between series comprising a grey relational system (Rajesh et al., 2015), it can solve the problem of stope structure parameters, for both the stability of the pillar and the ore recovery are considered. Therefore, the grey relational analysis is selected to study the stope structure parameters optimization (Zuo et al., 2016).

In this study, the setting of influencing factors was accomplished using the four factors four levels Taguchi experiment design method. Then the three dimensional model was established by software ANSYS (Manouchehrian et al., 2015), the maximum tensile strength, maximum compressive strength and ore recovery rate of each scheme were obtained. On the basis of the simulation results, the sequence and grade for each factor to the multi quality characteristics can be obtained by using grey relational analysis (Nelabhotla et al., 2016). All of the work above can provide great references value for further optimization of stope structure parameters, which can ensure safety and high efficiency mining.

2. Experimental procedure and operating parameters

It is well known that Bainiu mine is the biggest silver metal mine area in China, and the third all over the world, the resource reserves are abundant. The mineral deposit is mainly composed of silver, and associated with copper, lead, zinc and many other polymetallic deposits, the grade of the ore body is complex and changing. Because the ore mineralization is in the fractured zone, the ore body presents the characteristics of poor continuity, fractured rock mass and etc.. The technical conditions is poor, thickness of the ore body is 2~5 m in general, the angle of the ore body is 20~35°, which belongs to the inclined ore body. The room and pillar mining method is adopted to the Bainiu mine, in order to maintain the stability of the roof, the pillar is needed to support it. Moreover, the fractured rock mass may induce the pillar support function weakened in deep mining, the pillar is easy to collapse, it is bad for the safety production at the mine (Mallı et al., 2017). Therefore, the problem of safety and efficiency with inclined thin ore body in deep mining is an important issue in the mine.

On the basis of saint venant principle, the ore body mining has an effect on the 3~5 times of its boundary rock masses, so the range of the model is determined to be: long × width × height = 500 m×500 m×625 m, the established model is shown in Fig. 1 and Fig. 2, the thickness of the ore body is 13.5~27 m, and the experiment stope is on the level 1480 m, the surface level was 980 m. The model is established in the Finite element software ANSYS, and the simulation depth is 500 m. According to the technical conditions of Bainiu mine, the width of the ore block is selected to be 25 m, the length of the ore block is selected to be 40 m. Layout of the extraction process of ore blocks is shown in Fig. 2, the stopping sequence must follow the principle of “take one every the other one”, also continuous strip pillars are reserved, the room between strip pillar is extracted first, then on the continuous pillar stoping, finally, a series of points pillars are left.

The boundary condition of the model is as follow: displacement and stress boundary constraints are applied to the pre, post, left, right and bottom surface of the model. The top of the model is surface, so it is set to be the free boundary (Chen et al., 2001). The initial vertical stress is 13.5 MPa, and the horizontal stress is 1.1 times that of the vertical stress.

The main lithology in Bainiu mine is composed of argillaceous limestone rock, mudstone, siltstone and ore body, all of them are belonged to the elastic-plastic model, so the Drucker-Prager plastic yield criterion model is adopted for the calculation. According to the site engineering, geological investigation, the mechanical and physical properties are obtained by the laboratory tests, and Hoek-Brown strength criterion is used for weakening the rock mass to a certain extent, then the mechanical properties of argillaceous limestone rock, mudstone, siltstone and ore body are obtained, which is shown in Table 1.

To find out the relationship between the responses (the maximum tensile strength, the maximum compressive strength and ore recovery rate) and four stope structure parameters (stope height, pillar diameter, pillar spacing and pillar array pitch) of the optimization in broken rock conditions, experiments were planned according to four factors and four levels Taguchi orthogonal experiments. The range of values of the four influencing factors was defined as follows: stope height is 2.5~5.5 m, pillar diameter is 2.5~5.5 m, pillar spacing is 2~5 m, and pillar array pitch is 4~7 m. As it is shown in Table 2, the coded and actual values of influencing factors were given. By three-dimensional simulation tests, the effect of four influencing factors to the stope stability and ore recovery rate can be obtained.

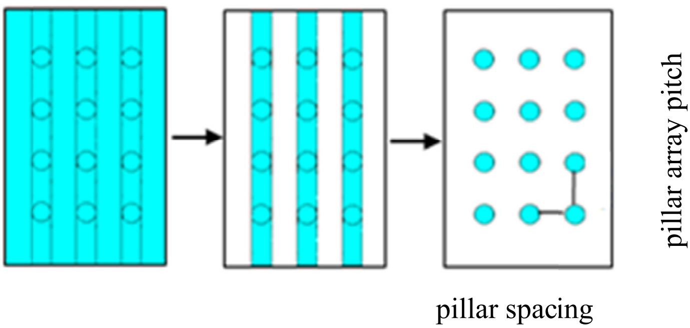

Fig. 1. Extraction process of ore blocks

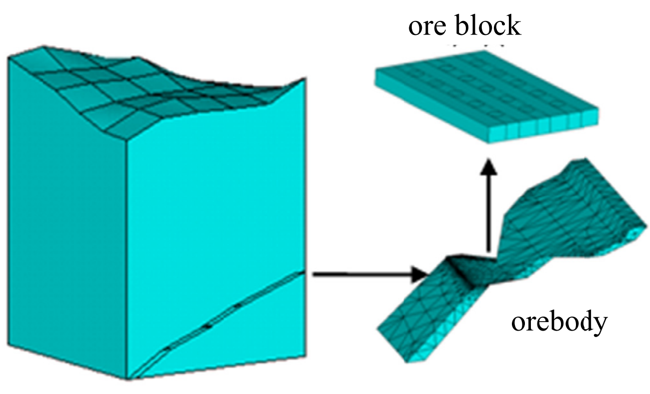

Fig. 2. Finite element model

TABLE 1

Rock mass physical and mechanical parameters

Lithology	Compressive stress /MPa	Tensile stress /MPa	Cohension /MPa	Friction angle /°	Elasticity Modulus /GPa	Density /g·cm^{-3}	Poisson ratio
Muddy limestone	45.43	4.02	3.47	28.38	9.37	2.74	0.25
Mudstone	35.21	2.01	1.14	17.79	4.51	2.79	0.19
Siltstone	79.89	2.98	4.08	35.97	14.88	2.64	0.27
Orebody	98.6	4.56	6.58	42.93	12.60	4.00	0.22

TABLE 2

Influencing factors and design levels

Symbol	Factors	Level 1	Level 2	Level 3	Level 4
A	Stope height/m	2.5	3.5	4.5	5.5
B	Pillar diameter/m	2.5	3.5	4.5	5.5
C	Pillar spacing/m	2	3	4	5
D	Pillar array pitch/m	4	5	6	7

3. Grey relational analysis

Grey system is the not fully known information system, that is to say, partial of the information is known, and partial of the information is unknown. Grey relational analysis is one of the most important parts of grey system theory, which is the method to the associated degree of various influencing factors in the system. GRA utilizes the mathematical method to analyze correlations between series comprising a grey relational system. By applying the GRA algorithm, every scheme can be ranked according to grey relational grades. Different alternatives of the influencing factors can be ranked by the grey relational grades of different series, and the rank shows that if the rank value is higher, it indicates superior alternatives.

3.1. Data pre-processing

Based on the grey theory, the grey correlation degree was adopted to reflect the degree of correlation between influencing factors, according to the development trend of similar or dissimilar degree. In general, the different evaluation indexes have different physical meaning and its dimension, when the range of the sequence is too large or too small, the function of factors would be neglected. If the influencing factors and goals are different, it may induces in correct results, in order to eliminate the dimensions of different factors, prior to the grey relational analysis, it is needed to process the original data. Because there is obvious tendency about the selected parameters, the indexes are needed to be normalized (Hao et al., 2015).

In order to eliminate the errors when processing data, the original sequence data are transferred to a comparable sequence. All of the experimental results are normalized in the range between zero to one. The data which are needed to normalization can be divided into four types, that is "the-larger-the-better", "the-smaller-the-better", "the fixed type" and "the interval type" (Rajesh et al., 2013).

If the original sequence belongs to the ‘‘the-larger-the-better’’ type, then the original sequence can be normalized as follows:

$$x_i^*(k) = \frac{x_i^0(k) - \min x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{1}$$

where $x_i^*(k)$ is the value after the grey relational generation (data pre-processing), $x_i^0(k)$ is the target attribute value, max $x_i^0(k)$ is the largest value of $x_i^0(k)$ and min $x_i^0(k)$ is the smallest value of $x_i^0(k)$.

If the original sequence belongs to “the-smaller-the-better” type, then the original sequence should be normalized as follows:

$$x_i^*(k) = \frac{\max x_i^0(k) - x_i^0(k)}{\max x_i^0(k) - \min x_i^0(k)} \tag{2}$$

However, if the original sequence belongs to “the fixed type”, the original sequence will be normalized by the forms as follows:

$$x_i^*(k) = 1 - \frac{|\ x_i^0(k) - x_i^0\ |}{\max x_i^0(k) - x^0} \tag{3}$$

With regard to the “interval type”, the original sequence can be simply normalized by the forms as follows:

$$x_i^*(k) = \begin{cases} 1 - \dfrac{q_{1j} - x_i^0(k)}{\max\left\{q_{1j} - \min x_i^0(k), - \max x_i^0(k) - q_{2j}\right\}}, & x_i^0(k) < q_{1j} \\ 1, \quad a_{ij} \in [q_{1j,} q_{2j}] & \\ 1 - \dfrac{x_i^0(k) - q_{2j}}{\max\left\{q_{1j} - \min x_i^0(k),\ \max x_i^0(k) - q_{2j}\right\}}, & x_i^0(k) > q_{2j} \end{cases} \tag{4}$$

where $[q_{1j}, q_{2j}]$ is the best stable interval range of j index.

During this investigation, “the-smaller-the-better” is selected for the maximum tensile strength and maximum compressive strength and ‘‘the-larger-the better’’ case is selected for the ore recovery. The stope structure parameters are optimized by four factors and four level orthogonal experiments, Table 3 lists the influencing factors, their levels and the values of multiple quality characteristics. In this study, the stope height, pillar diameter, pillar spacing and pillar array pitch are selected for the influencing factors, the quality characteristics include maximum tensile strength, maximum compressive strength and ore recovery. The pre-processing results of the normalization sequences of each performance characteristics are shown in Table 4.

TABLE 3

Experimental results for control factors and multiple performance data

No.	Coded level of parameters				Actual level of parameters				Observed		
	A	B	C	D	Stope height /m	Pillar diameter /m	Pillar spacing /m	Pillar array pitch /m	Maximum tensile strength /MPa	Maximum compressive strength /MPa	Ore recovery rate/%
1	1	1	1	1	2.5	2.5	2	4	4.43	131.79	83.23
2	1	2	2	2	2.5	3.5	3	5	3.46	102.28	82.60
3	1	3	3	3	2.5	4.5	4	6	4.06	141.11	82.19
4	1	4	4	4	2.5	5.5	5	7	6.22	248.28	81.91
5	2	1	2	3	3.5	2.5	3	6	4.26	129.71	89.51
6	2	2	1	4	3.5	3.5	2	7	4.78	146.84	83.35
7	2	3	4	1	3.5	4.5	5	4	4.55	153.15	80.31
8	2	4	3	2	3.5	5.5	4	5	3.63	122.08	76.19
9	3	1	3	4	4.5	5.5	4	7	5.69	190.88	80.00
10	3	2	4	3	4.5	3.5	5	6	5.82	193.56	88.09
11	3	3	1	2	4.5	4.5	2	5	4.01	101.63	74.26
12	3	4	2	1	4.5	5.5	3	4	4.08	109.24	70.59
13	4	1	4	2	5.5	2.5	5	5	7.78	244.91	91.28
14	4	2	3	1	5.5	3.5	4	4	6.21	162.48	82.90
15	4	3	2	4	5.5	4.5	3	7	6.82	194.67	81.57
16	4	4	1	3	5.5	5.5	2	6	6.37	184.84	72.47

TABLE 4

Sequences of each performance characteristic after data pre-processing

No.	Maximum tensile strength	Maximum compressive strength	Ore recovery rate
Reference sequence	1.0	1.0	1.0
1	0.777	0.794	0.611
2	1.000	0.996	0.580
3	0.862	0.731	0.561
4	0.362	0.000	0.547
5	0.815	0.809	0.914
6	0.694	0.692	0.617
7	0.748	0.649	0.470
8	0.961	0.861	0.271
9	0.483	0.391	0.455
10	0.454	0.373	0.846
11	0.873	1.000	0.177
12	0.857	0.948	0.000
13	0.000	0.023	1.000
14	0.363	0.585	0.595
15	0.221	0.366	0.531
16	0.326	0.433	0.091

3.2. Grey relational coefficient and grey relational grade

Following data pre-processing, a grey relational coefficient is calculated to express the relationship between the ideal and actual normalized experimental results. In order to determine grey relational difference information space of the matrix, the formulation to calculate the difference information can be expressed as follows (Kumar et al., 2015):

$$\Delta_{0i}(k) = \left\| x_0{}^i(k) - x_i{}^*(k) \right\| \tag{5}$$

where $x_i^*(k)$ is the comparability sequence. Therefore, the $\Delta_{0i}(k)$ can be obtained from the formula (5), the maximum and minimum of the elements can be extracted from the data $\Delta_{0i}(k)$, which can be expressed by the formula (6) and formula (7):

$$\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \left\| x_0{}^*(k) - x_j{}^*(k) \right\| \tag{6}$$

$$\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \left\| x_0{}^*(k) - x_j{}^*(k) \right\| \tag{7}$$

Then the distance between every compared point and the reference point should be found, the differentiation and the correlation of the influencing factors are found by integral analysis. The correlation coefficient can express the correlation between compared factors and correlative factors, which is shown as follows (Aslan et al., 2012):

$$\xi_i(k) = \frac{\Delta_{\min} + \xi \cdot \Delta_{\max}}{\Delta_{0i}(k) + \xi \cdot \Delta_{\max}} \tag{8}$$

where $\xi(k)$ is grey correlation coefficient, $\Delta_{0i}(k)$ is the relation sequence of the reference sequence $x_0^i(k)$, ξ is identification coefficient, the function of it ξ is to improve difference of significance between correlation coefficient, $\xi \in [0,1]$, the calculated grey coefficient is employed by choosing $\xi = 0.5$ in general(Deepanraj et al., 2012).

To get the grey relational coefficient, the average of grey relational coefficients is usually applied to calculate it, so the relevance of influencing factors can be compared, the grey relation coefficient can be calculated by the formula (9):

$$\gamma_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k) \tag{9}$$

where n is the quality number, γ_i is the grey relational grade of each experiment , the range of γ_i is from zero to one. In the grey relation coefficient sequence, the relational grade shows the important relationships among the sequence, if the correlation of influencing factors is relatively larger, it indicates that the influencing factor has greater influence on the assessment index, that is to say the sensibility would be larger. Otherwise, it would be less sensitive.

In the grey relational analysis, the grey relational grade is used for showing the relationship among the sequences. If the two sequences are identical, then the value of the grey relational grade is equal to 1. The grey relational grade also indicates the degree of influence that the comparability sequence could exert over the reference sequence. Therefore, if a particular comparative sequence is more important than the other comparability sequences to the reference sequence, then the grey relational grade for that comparability sequence and reference sequence will be higher than other grey relational grades.

TABLE 5

The deviation sequences

No.	Maximum tensile strength	Maximum compressive strength	Ore recovery rate
Reference sequence	1.0	1.0	1.0
1	0.223	0.206	0.389
2	0.000	0.004	0.420
3	0.138	0.269	0.439
4	0.638	1.000	0.453
5	0.185	0.191	0.086
6	0.306	0.308	0.383
7	0.252	0.351	0.530
8	0.039	0.139	0.729
9	0.517	0.609	0.545
10	0.546	0.627	0.154
11	0.127	0.000	0.823
12	0.143	0.052	1.000
13	1.000	0.977	0.000
14	0.637	0.415	0.405
15	0.779	0.634	0.469
16	0.674	0.567	0.909

4. Results and discussion

To determine the performance of the stope structures in broken rock conditions, the GRA method was first applied to optimize the stope structure parameters. In all of the three quality characteristics, the maximum tensile strength and maximum compressive strength are selected for the case of "the-smaller-the-better" and the ore recovery rate was selected for the case of "the-larger-the-better". By using the orthogonal experiments of four factors and four levels, 16 experiment tests were conducted to reflect the four influencing factors to the quality characteristics of stope structure parameters in total. Firstly, the quality characteristics were normalized, then the GRA mathematical conversion was used for obtaining the comparable coefficients and grades. All of the comparable coefficient were ranked, so the effect contribution of each influencing factor to the quality characteristics can be known.

Calculated grey relational coefficients and grey relational grade are shown in Table 4, According to it, the stope structural parameter setting for the second experiment has the highest grey relation grade, indicating that the optimal stope structure parameters are obtained with the combination of A2B3C2D2. In terms of grey relational grades, the second on the Table 4 is the fifth experiment, the third is the eleventh experiment. The grey relational grade is calculated by the average of grey relation coefficient of the quality characteristics, average grey relational grade for each parameter level can be calculated by the data of the average for the same level. For example, the grey relational grades factor A at level 1, B at level 1, C at level 1 and D at level 1 are calculated as follows:

$$\gamma_{A1} = \frac{1}{4}(0.654 + 0.845 + 0.655 + 0.432) = 0.647$$

$$\gamma_{B1} = \frac{1}{4}(0.654 + 0.769 + 0.474 + 0.557) = 0.613$$

$$\gamma_{C1} = \frac{1}{4}(0.654 + 0.602 + 0.725 + 0.416) = 0.599$$

$$\gamma_{D1} = \frac{1}{4}(0.654 + 0.579 + 0.672 + 0.513) = 0.605$$

TABLE 6

Calculated grey relational coefficients and grey relational grade

No.	Grey relation coefficient			Grey relational grade	Orders
	Maximum tensile strength	Maximum compressive strength	Ore recovery rate		
1	0.691	0.709	0.562	0.654	7
2	1.000	0.991	0.544	0.845	1
3	0.783	0.650	0.532	0.655	6
4	0.439	0.333	0.525	0.432	15
5	0.730	0.723	0.854	0.769	2
6	0.621	0.619	0.566	0.602	8
7	0.665	0.587	0.485	0.579	9
8	0.928	0.782	0.407	0.706	4
9	0.492	0.451	0.478	0.474	13
10	0.478	0.444	0.764	0.562	10
11	0.797	1.000	0.378	0.725	3
12	0.778	0.906	0.333	0.672	5
13	0.333	0.339	1.000	0.557	11
14	0.440	0.546	0.553	0.513	12
15	0.391	0.441	0.516	0.449	14
16	0.426	0.468	0.355	0.416	16

The grey relational grade for each parameter level and its grey relational grade are shown in Table 6, Also the difference between maximum grey relational grade and minimum relational grade are listed in the Table 7, if the data of the difference between maximum grey relational grade and minimum relational grade is larger, it means the comparability sequence is closely correlated with the reference sequence. From the results of the grey correlation analysis, the highest grey relation grade is A2B2C2D2, that is to say the optimal stope structure parameters combination is A2B2C2D2, the stope height is 3.5 m, pillar diameter is 3.5 m, pillar spacing is 3 m and pillar array pitch is 5 m.

TABLE 7

The response table for grey relational analysis

Symbol	Average grey relational grade for each parameter level					Rank
	Level 1	**Level 2**	**Level 3**	**Level 4**	**Max-min**	
A	0.647	$0.664^{\#}$	0.608	0.484	0.180	2
B	0.613	$0.630^{\#}$	0.602	0.557	0.074	4
C	0.599	$0.684^{\#}$	0.587	0.533	0.151	3
D	0.605	$0.708^{\#}$	0.601	0.489	0.219	1

Comments: # represents optimal level of each parameter.

The influence of stope structure parameters with four levels for each quality characteristics are shown in Fig. 3 and Fig. 4. Table 7 lists the difference between the maximum grey relation grade and minimum grey relation grade, all of the difference are positive, which indicates that the four influencing factors have great effect on the quality characteristics. This difference can be defined as the effect contribution of the influencing factors. From the results, it can be seen that the first effect value of 0.219 is the pillar array pitch, the second effect value of 0.180 is the stope height, the third effect value of 0.151 is the pillar spacing, the fourth effect value of 0.074 is the pillar diameter.

On the basis of the analysis results above, by adopting grey relational analysis to optimize stope structure parameters based on the quality characteristics of maximum tensile strength, maximum compressive strength and ore recovery. The data pre-processing, effect of each influencing factors on the quality characteristics and grey relational coefficient are all obtained. It indicates that the pillar array pitch has a high value, it has a significant effect on the stability of ore pillar and recovery ore as much as possible. The optimal stope parameters are as follows: the stope height is 3.5 m, the pillar diameter is 3.5 m, the pillar spacing is 3 m and the pillar array pitch is 5 m, .the maximum tensile strength of the pillar is 3.46 MPa, the maximum compressive strength is 102.8 MPa, the ore recovery is 82.6%, the maximum tensile strength is smaller than the tensile strength of the rock mass, also the maximum compressive strength

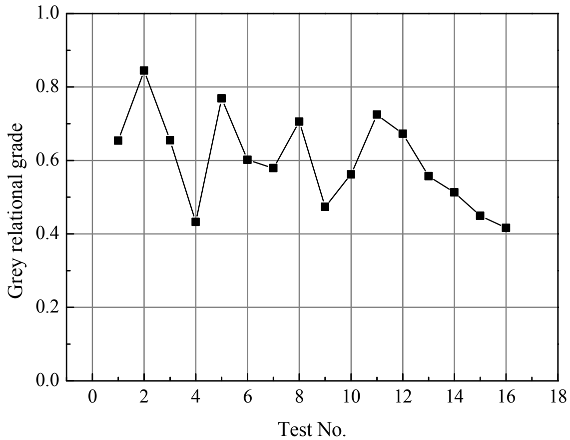

Fig. 3. Graph of grade relational grades

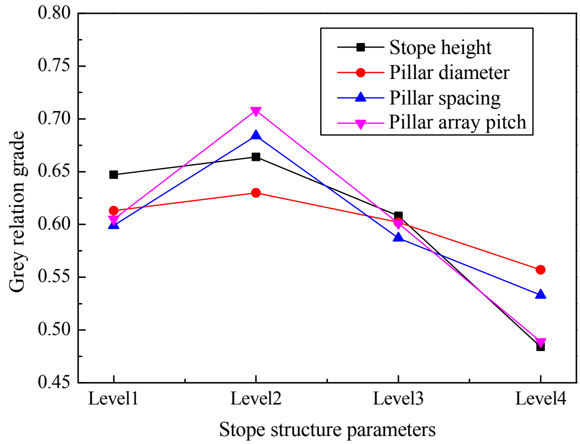

Fig. 4. Grey relational grade for the stope parameter levels

is smaller than the compressive strength of the rock mass, the ore can be recycled to a certain extent. On one hand, it can ensure the stability of the ore pillar, on the other hand, it can recycle ore as much as possible.

According to the technical conditions of the level 1480 m in Bainiu mine, the designed stope parameters is shown as follows: the height of the stope is 3.5 m, the pillar diameter is 3.5 m, the pillar spacing is 3 m, and the pillar array pitch is 5 m. The blasting method in the stope is ordinary blasting method, the stability of pillar is easily affected by the blasting vibration. In-situ measurement shows that only a small number of the pillars with few joints and fissures development appear wall caving and peeling off, all of the pillars can basically remain stable. In addition, ore recovery rate can be ensured to be more than 82%.

5. Conclusion

This paper presents a novel method for the optimization of stope structure parameters with multiple performance characteristics based on the grey relational analysis. The numerical model was established in the software ANSYS, on the basis of the simulation results, the Taguchi experimental design method and the grey relational analysis method were applied to evaluate the effect of influencing factors on safety and efficiency mining. As a result, some conclusions can be summarized as follows:

(1) With a larger pillar diameter, smaller pillar spacing and pillar array pitch, the ore recovery rate will be low, on the contrary, the stability of the pillar will decrease, the probability of ground pressure activities increases, which is a serious threat to the safety production.

(2) The grey relational grade shows that the pillar array pitch has the most noticeable effect on the stability of the pillar and ore recovery rate, the second effect is the stope height, the third effect is pillar spacing, while the pillar diameter has the lowest effect on it.

(3) The optimized stope parameters for the Bainiu mine is shown as follows: the height of the stope is 3.5 m, the pillar diameter is 3.5 m, the pillar spacing is 3 m, and the pillar

array pitch is 5 m. The in-situ measurement shows that all of the pillars are basically stable, the ore recovery rate can reach more than 82%. It indicates that the optimization of multiple performance characteristics can be greatly simplified through the grey relational analysis method. This method has the characteristics of high efficiency, the results is accurate, for it can provide certain guiding significance for the stope structure parameters in the mine.

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