Bivariate Multivariate Nonlinear Prediction Model for the Depth of Damaged Floor in Working Area Based on MATLAB

Qu Xingyue[1,2], Shi Longqing[1,2*], Xu Dongjing[1,2], Qin Daoxia[3]

[1]Shandong Provincial Key Laboratory of Depositional Mineralization & Sedimentary Minerals, Qingdao 266590, China; 2College of Earth Sciences & Engineering, Shandong University of Science and Technology, Qingdao 266590, China; 3Feicheng Mining Group Shanxian County Energy Co., Ltd., Heze, Shandong 274300, China.

Abstract

In the process of coal seam mining, the water-resisting strata under coal seam floor deform, and then produce floor heave and cracks, which makes the underground water stored in aquifers under the coal seam floor pour into the mine, causing water inrush accidents. Therefore, the depth of damaged floor is the key data to evaluate the water resistance performance of rock strata under coal seam floor. Aimed at the influences of various complicated factors for damaged floor during coal mining, the prediction for the depth of damaged floor in working area is regarded as a pattern recognition problem with nonlinear, multi dimensions and finite samples. A bivariate multivariate non-linear model for predicting the depth of damaged floor based on MATLAB was constructed. Six factors were selected as indices to evaluate the depth of damaged floor. Based on factor analysis theory, three exogenous latent variables of structural equation model were determined by dimensionality reduction. On this basis, MLP neural network and Deng's grey correlation were used to calculate weights of main controlling factors, then the combined weights of three exogenous latent variables were solved by conflicting evidence fusion. Structure optimal bivariant multivariate nonlinear regression modified model. Taking the No. 2_1 coal seam mining of Shanxi Formation in Guhanshan coal mine as an example, predict its depth of damaged floor, then auxiliarily prove the accuracy of the bivariate multivariate nonlinear regression modified model by Flac3D numerical simulation.The results show that the bivariate prediction model has higher accuracy rate, providing theoretical basis for preventing water inrush from coal seam floor.

Keywords: depth of damaged floor; bi-variable; multivariate nonlinear prediction

Introduction

In China's coal industry, North China is an important coal-producing area in China. It has complex geological and hydrogeological conditions. Especially in the process of coal seam mining, the water-resisting strata under coal seam floor deform, and then produce floor heave and cracks, which makes the underground water stored in aquifers under the coal seam floor pour into the mine, causing water inrush accidents. Therefore, the depth of damaged floor is the key data to evaluate the water resistance performance of rock strata under coal seam floor. In the past, emprical formulas in regulations were usually used to calculate the depth of damaged floor, however, in these formulas, only mining depth, dip angle and facing length were considered. In practical situation, there are many factors affecting the depth of damaged floor. Thus, the author comprehensively considered the factors which have direct influence on the depth of damaged floor, including, mining thickness, dip angle, mining depth, facing length and destruction resistance of the floor strata, improving the traditional empirical formulas and providing theoretical and field basis for preventing water inrush from coal seam floor (Shi et al. 2004; Xu et al. 2012).

Qu Xingyue: 1635599892@qq.com; *Corresponding Author.: 0532-80691759; Email address: cattony 2002@163.com.

Study Area

The Guhanshan coal mine is located in the centre of the Jiaozuo coal field, about 25 km apart from Jiaozuo city, Shandong province, in eastern China. The mine is irregularly developed, covering an area of around 17.00 km². The mine is found in a monocline dipping gently SE, (<25°), with mainly SSE and NNW striking faults thatare well developed in this area (Fig 1). According to the borehole data, the lithology in thestudy area consists of Tertiary(R), Quaternary (Q), Permian (P), Carboniferous (C), and Ordovician (O) strata from top to bottom (Zhang et al. 2017; Gong et al. 2012).

Water-inrush mechanism caused by damaged floor

With the advancing of the working face, there are four layer-belts existing in rock formations below coal seam floor (Fig 2), i. e. broken zone caused by mine pressure, the new damaged zone, the original damaged zone and the original water flowing crevice zone. Under the condition of long-term tectonic movement, minor faults and joint fissures well-developed in damaged zone extend continually. The continuity of rock formations in broken zone caused by mine pressure was completely destroyed, and the rock formations lost their water-resisting property entirely. Therefore, once the broken zone caused by mine pressure connected with cracks well-developed in damaged zone, floor water will gush along these layer-belts, causing mine water inrush accidents. The pattern of water inrush is shown in Fig 2. Therefore, accurate prediction for depth of damaged floor is of great significance for preventing water inrush from coal seam floor.

Factor Analysis

Using SPSS factor analysis modeling, 28 groups of measured data of the depth of damaged floor were analyzed by factor analysis, as shown in Fig 3. As can be seen from Fig 3, the fault influencing factors (E) and the dip angle ( ) have higher load values on the first principal component, which are described as Factor 1. The facing length (L) and the destruction resistance of the floor strata (D) have higher load values on the second principal component, which are described as Factor 2. The mining thickness (M) and the mining depth (H) have higher load values on the third principal component, which are described as Factor 3 (Wang et al. 2019). In other words, that is to determine the three major exogenous latent variables of the structural equation model, as shown in Fig 4. Based on Matlab programming, the correlations between the three major exogenous latent variables and their internal factors were determined, as shown in Fig 5.

Weights of Main Controlling Factors

Determining Weights of Main Controlling Factors by MLP Neural Network

The following indicators were used to describe the results, as shown in Table 1, the standardized weight distribution of main controlling factors was obtained as shown in Fig 6 (Sun et al. 2001).

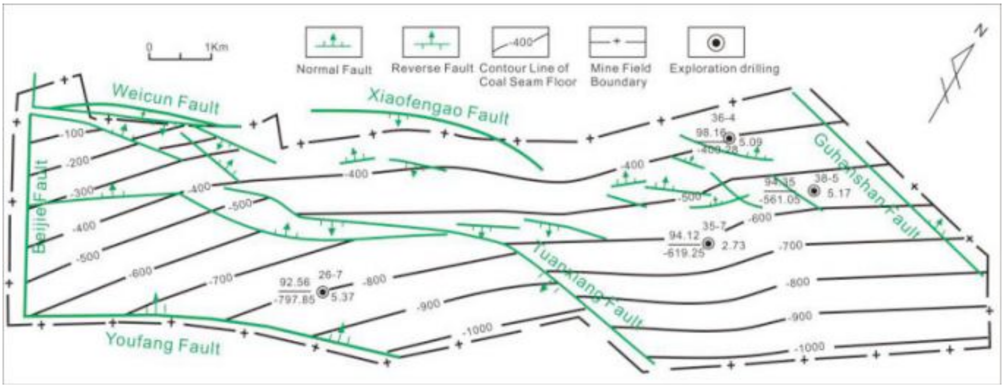


Figure 1 Structure outline map of Guhanshan Mine

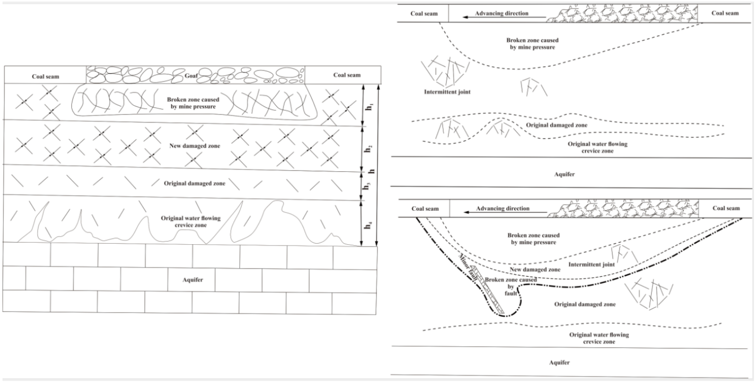
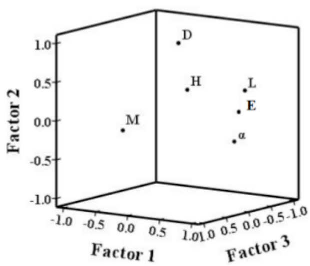


Figure 2 *Water-inrush mechanism*



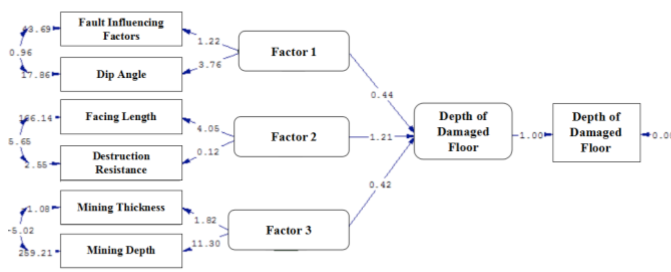


Figure 3 *Rotated composition diagram* *Figure 4* *The path diagram of the structural equation model*

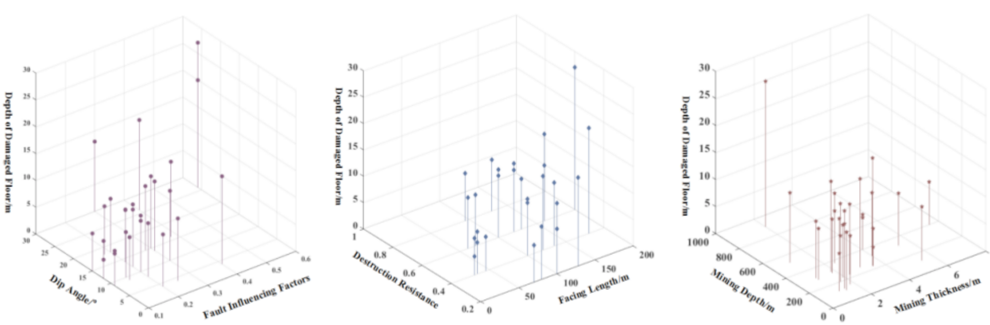


Figure 5 *The cubic diagrams of correlations between the three major factors and their internal factors*

1) Relevant prominence coefficient:

$$\begin{cases} r_{ij} = \sum_{k=1}^{p} w_{ki}\left(1-e^{-x}\right)/\left(1+e^{-x}\right) \\ x = w_{jk} \end{cases};$$

2) Correlation index: $\begin{cases} R_{ij} = \left|\left(1-e^{-y}\right)/\left(1+e^{-y}\right)\right| \\ y = r_{ij} \end{cases}$;

3) Absolute influence coefficient: $S_{ij} = R_{ij} / \sum_{i=1}^{m} R_{ij}$

Where i is the input unit; j is the output unit; k is the hidden unit; w_{ki} is the weight coefficients between i and k; w_{jk} is the weight coefficients between j and k.

Determining Weights of Main Controlling Factors by Deng's Grey Relation

Determine the grey association set X of the nondimensionalized parent sequence and subsequence as follows (Qiu et al. 2016).

$$X = \left(X_0, X_1, \cdots, X_n\right) = \begin{pmatrix} x_0(1) & x_1(1) & \cdots & x_n(1) \\ x_0(2) & x_1(2) & \cdots & x_n(2) \\ \vdots & \vdots & \vdots & \vdots \\ x_0(n) & x_1(n) & \cdots & x_n(n) \end{pmatrix}$$

Table 1 *Weights of main controlling factors determined by MLP neural network*

Main controlling factors	E	∝	L	D	M	H
Weights W_1	0.571	0.032	0.103	0.022	0.031	0.241

Then we can define the correlation coefficient of the x_0 and x_i at the point k as follows (Qiu et al. 2016).

$$\xi(k) = \frac{\min_i \min_t |x_0(k) - x_i(k)| + \rho \cdot \max_i \max_t |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \cdot \max_i \max_t |x_0(k) - x_i(k)|}$$

Where ρ is the resolution ratio, normally $\rho = 0.5$. According to $\overline{\omega_j} = \frac{1}{n}\sum_{i=1}^{n} \xi_{ij}\left(j = 1,2,\cdots,n\right)$, the weights W2 of each evaluation index we determined as shown in Table 2.

Coupling Weights of Main Controlling Factors by Conflicting Evidence Theory

Determine the initial weight matrix A of main controlling factors as follows (Zhang et al. 2018):

$$A = \begin{pmatrix} 0.571 & 0.032 & 0.103 & 0.022 & 0.031 & 0.241 \\ 0.191 & 0.169 & 0.182 & 0.159 & 0.143 & 0.156 \end{pmatrix}$$

The matrix ρ = (0.381 0.1005 0.1425 0.0905 0.087 0.1985) was obtained, and then the mean matrix B was obtained as follows.

$$B = \begin{pmatrix} 0.476 & 0.066 & 0.123 & 0.056 & 0.059 & 0.220 \\ 0.286 & 0.135 & 0.162 & 0.125 & 0.115 & 0.177 \end{pmatrix}$$

Solve D-value matrix

$$\lambda = \begin{pmatrix} 0.499 & 0.682 & 0.277 & 0.757 & 0.644 & 0.214 \\ 0.499 & 0.682 & 0.277 & 0.757 & 0.644 & 0.214 \end{pmatrix}$$

according to formula $\lambda_{ij} = \frac{|a_{ij} - p_j|}{p_j}$.

Then the unauthentic vector C and credibility vector were gained (Zhang et al. 2018).
C = (0.5 0.5) C′ - (0.5 0.5)
Based on this, we can determine the initial weight credible matrix A' and weight unauthentic matrix A''. Ultimately, we can get the comprehensive weight matrix I and optimizational weight matrix I'' as follows.

$$A' = \begin{pmatrix} 0.286 & 0.016 & 0.052 & 0.011 & 0.016 & 0.121 \\ 0.096 & 0.085 & 0.091 & 0.080 & 0.072 & 0.078 \end{pmatrix}$$

$$A'' = \begin{pmatrix} 0.238 & 0.033 & 0.061 & 0.028 & 0.030 & 0.110 \\ 0.143 & 0.067 & 0.081 & 0.062 & 0.058 & 0.089 \end{pmatrix}$$

$$I = \begin{pmatrix} 0.524 & 0.049 & 0.113 & 0.039 & 0.045 & 0.230 \\ 0.239 & 0.152 & 0.172 & 0.142 & 0.129 & 0.167 \end{pmatrix}$$

$$I'' = \begin{pmatrix} 0.729 & 0.018 & 0.059 & 0.013 & 0.014 & 0.167 \\ 0.484 & 0.081 & 0.131 & 0.068 & 0.060 & 0.176 \end{pmatrix}$$

The optimal weights were fused according to the formula

$$w = \frac{\sum_{\cap I_{ji} = I_i} \prod_{j=1}^{2} w_j\left(I_{ji}\right)}{1 - \sum_{\cap I_{ji} = \varnothing} \prod_{j=1}^{2} w_j\left(I_{ji}\right)}$$

, as shown in Table 3.

Nonlinear prediction model for the depth of damaged floor based on bi-variables

Based on MATLAB programming, three groups of relationships in Fig 5 were fitted, and the correlativity surfaces and residual analysis diagrams were obtained as shown in Fig 7, 8 and 9. The optimum surface equations between measured depth of damaged floor and bi-variables were determined as follows:
$De = a_1 + a_2E + a_3a$; $De = b_1 + b_2L + b_3D + b_4L^2 + b_5LD$

$De = c_1 + c_2M + c_3H + c_4M^2\ c_5MH + c_6H^2 + c_7M^3 + c_8M^2H + c_9MH^2$

On the basis of considering combined weights of principal factors, the established bivariant optimal surface equations were substituted into the SPSS statistical analysis software for bivariant multiple nonlinear

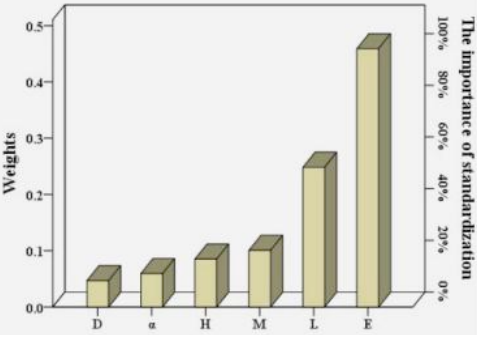


Figure 6 *Standardized weight distribution*

Table 2 *Weights of main controlling factors determined by Deng's grey relation*

Main controlling factors	E	∝	L	D	M	H
Weights W_1	0.191	0.169	0.182	0.159	0.143	0.156

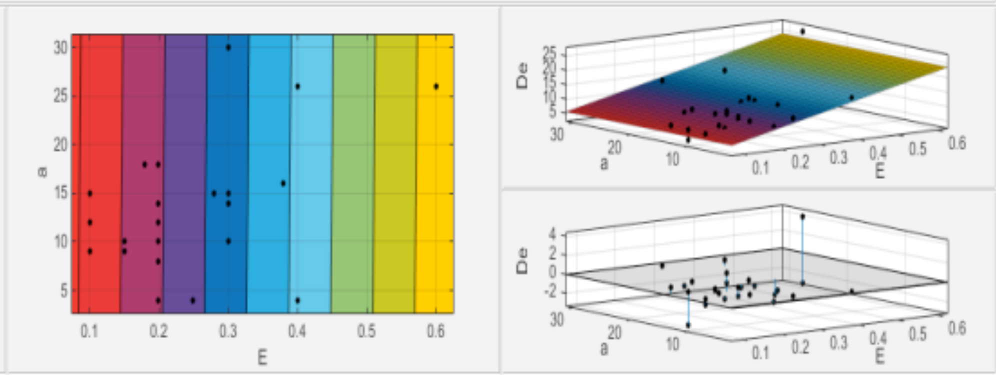


Figure 7 *Fitting of E and*

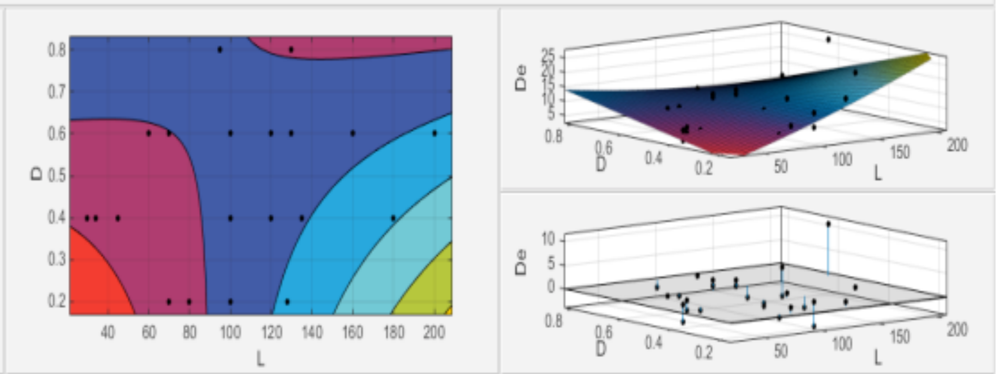


Figure 8 *Fitting of L and D*

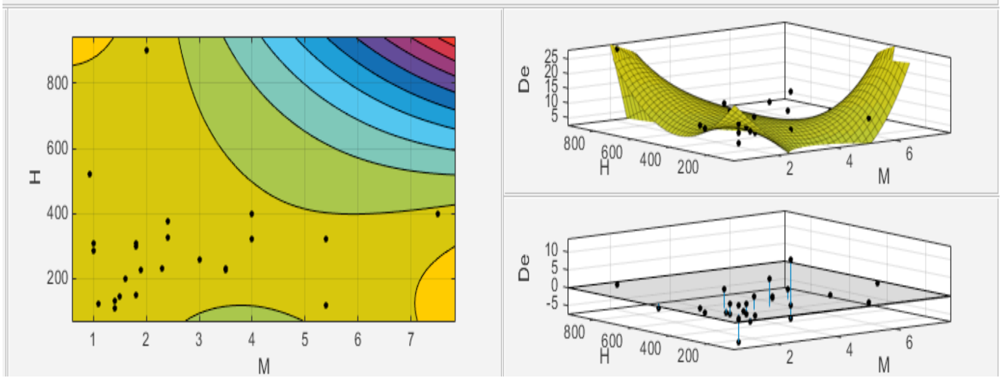


Figure 9 *Fitting of M and H*

Table3 Index *weights fused by conflicting evidence theory*

Main controlling factors	Optimized Weights		Weights fused by conflicting evidence
	MLPneural network	Deng's grey correlation	
E	0.571	0.191	0.527
∝	0.032	0.169	
L	0.103	0.182	0.274
D	0.022	0.159	
M	0.031	0.143	0.199
H	0.241	0.156	

regression analysis. The coefficients of each variable were recalculated to determine the bi-variables multiple nonlinear regression modified model for predicting depth of damaged floor as follows:

$$De = 22.83E - 0.004\propto + 0.057L - 2.05D - 0.0003L^2 + 0.005LD - 2.76M - 0.05H - 0.42M^2 + 0.031MH + 0.12M^3 - 0.003M^2 + 8.37$$

Based on the above formula, the depth of damaged floor of 15031, 15051, 15071 and 15091 working faces in Guhanshan Coal Mine was predicted, as shown in Table 4.

In order to further illustrate the feasibility of the bivariate multivariate nonlinear regression modified model for predicting depth of damaged floor, now, Flac3D three-dimensionalis program was adopted to simulate the depth of damaged floor of 15031 working face in Guhanshan Mine, as shown in Fig. 10. From the figure, it can be seen that the numerical simulation results are similar to the prediction results of the model established in this paper, which auxiliarily confirms the accuracy of the bivariate multivariate nonlinear regression modified model for predicting the depth of damaged floor.

Conclusions

(1) Considering six factors affecting depth of damaged floor comprehensively, we determined weights of main controlling factors based on MLP neural network and Deng's grey relation, and then coupled these weights by conflicting evidence theory, ensuring the effective evaluation of the relative importance of each indicator for the dynamic model.

(2) Based on the bivariate multivariate non-linear regression theory, a prediction model for the depth of damaged floor was established, and applied to the prediction of the depth of damaged floor in Guhanshan Coal Mine. Compared with the outcomes of Flac3D numerical simulation, the results show that the bivariant multiple regression equation have higher prediction accuracy, providing theoretical and field basis for preventing water inrush from coal seam floor.

Acknowledgments

The authors thank all the experts for their careful work and thoughtful suggestions. We gratefully acknowledge the financial support of the National Natural Science Foundation of China (41572244), (41807283) and (51804184).

References:

Shi LQ, Han J, Gao YF (2004). The study on the depth of destroyed stope floor. Journal of China Coal Society, 29(S): 1-4.

Xu RP, Jiang ZQ, Duan HF, et al. (2012). Research on numerical simulation and measurement of damage depth of seam floor under confined water action. Mining Safety and Environmental Protection, 39(3): 1-4.

Zhang H (2017). Study on primary factors and dominant direction of coal seam sermeability in the Guhanshan Coal Mine, Jiaozuo Mining Area. Henan Polytechnic University.

Gong PW (2012). Research on gas drainage technology at gob area of Guhanshan Coal Mine. Liaoning Technical University.

Wang DD, Shi LQ (2019). Source identification of mine water inrush: a discussion on the application of hydrochemical method. Arabian Journal of Geosciences, 12: 58.

Sun HJ, Wang XH (2001). Determination of the weight of evaluation indexes with artificial neural network method. Journal of Shandong University of Science and Technology (Natural Science), 03:84-86.

***Table 4** Prediction of depth of damaged floor in Guhanshan Mine*

Working faces	E	α	L	D	M	H	Predicted values
15031	0.40	11.3	120	0.3	2.3	435	14.79
15051	0.38	11.3	120	0.3	2.3	455	14.45
15071	0.42	11.3	120	0.3	2.3	475	15.47
15091	0.40	11.3	120	0.3	2.3	495	14.12

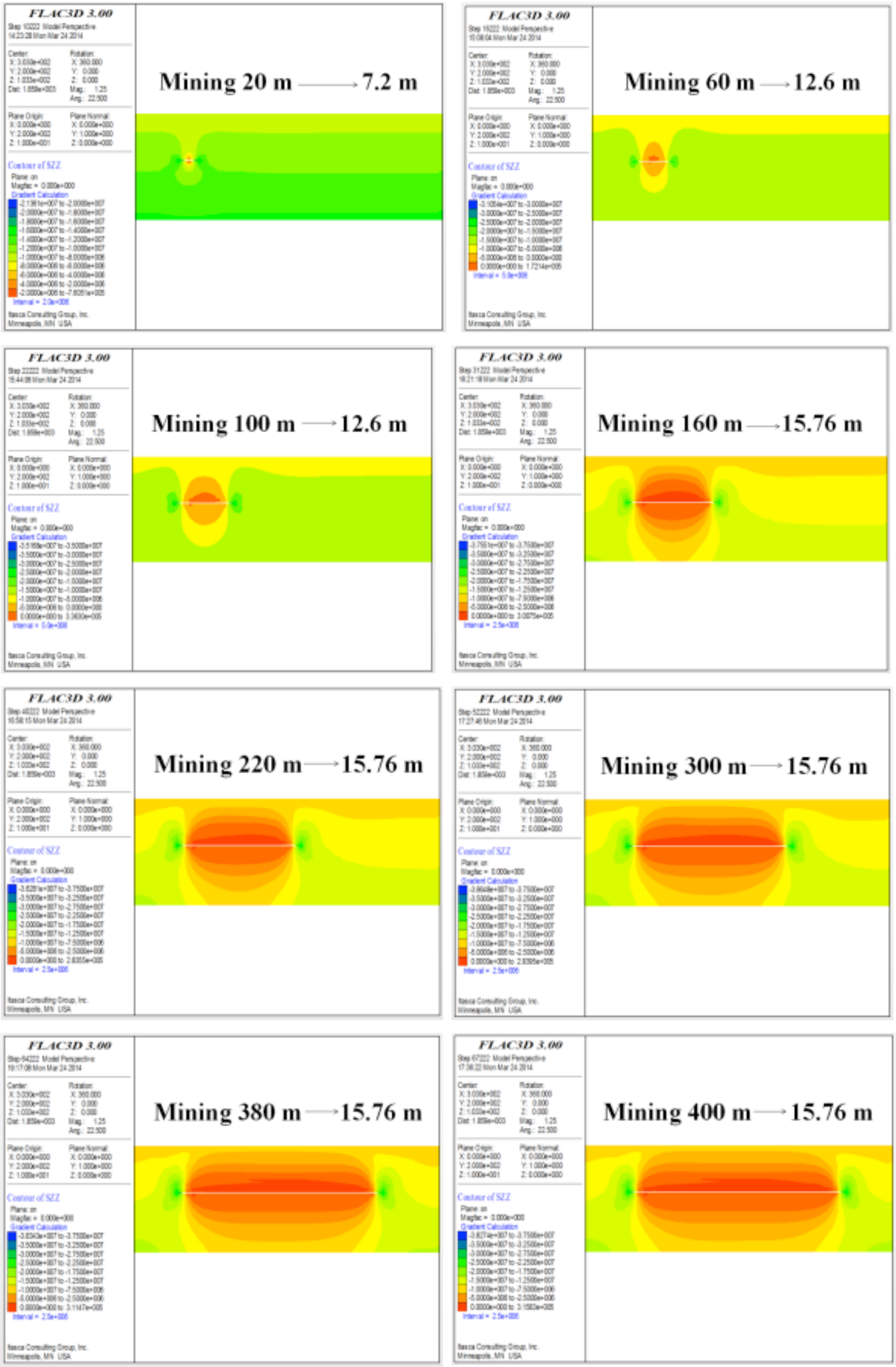


Figure 10 The numerical simulation of the depth of damaged floor

Qiu, M, Shi LQ, et al. (2016). Assessment of water inrush risk using the fuzzy delphi analytic hierarchy process and grey relational analysis in the Liangzhuang Coal Mine, China. Mine Water & the Environment, 36(1):1-12.

Zhang M, Zhai WP (2018). Application of improved D-S algorithm of conflict evidence to capacity evaluation. Journal of Henan University(Natural Science), (05).