

Article

An Improved Back Propagation Neural Network Based on Differential Evolution and Grey Wolf Optimizer and Its Application in the Height Prediction of Water-Conducting Fracture Zone

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Abstract: Given that the conventional back propagation neural network (BPNN) easily falls into the local optimal solutions, resulting in poor prediction accuracy, an improved BPNN based on the differential evolution and grey wolf optimizer (DEGWO) is proposed, the so-called DEGWO-BPNN. The prediction of the water-conducting fracture zone (WCFZ) height is significant for mine safety operations. A total of 104 sample data are trained and 25 sample data are tested to identify the optimal prediction model. Five evaluation indexes are selected to assess the prediction performance of the models quantitatively. Finally, the DEGWO-BPNN model is applied to a specific engineering case. The main conclusions are as follows: (1) Mining height, mining depth, coal seam dip, panel width, and ratio of hard rock as the main factors affecting the WCFZ height are selected. The topology structure of the model is defined as '5-12-1'; (2) the bias between the predicted value and the actual value of the training samples is smaller with an average error of 2.39. Test samples further validate the prediction precision through evaluation indexes. The values of MAE, RMSE, MAPE, and R^2 are 2.3952, 3.4674, 5.3148%, and 0.99077, respectively. The prediction accuracy is 94.6852%; (3) 'Mining Code', MLR, BPNN, and GWO-BPNN models are treated as the comparison groups. The comparative analysis shows that the prediction performance of 'Mining Code' is the worst, while that of DEGWO-BPNN is the best, and it outperforms other algorithms and statistical approaches; (4) the prediction of WCFZ height in the 11601 panel is in line with the actual value. The prediction error of the DEGWO-BPNN model is lower than that of the comparison models. As such, the DEGWO-BPNN model can be well applied to the prediction of WCFZ height and is suitable for coal mines with different regional geological conditions. It can provide a valuable reference for mine safety operations.

Keywords: differential evolution; grey wolf optimizer; DEGWO-BPNN; water-conducting fracture zone; prediction performance; evaluation indexes



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1. Introduction

Due to the slow progress in the development and utilization of non-fossil energy, energy consumption is still dominated by fossil energy such as coal, oil, and natural gas in China [1]. Based on the data from the National Bureau of Statistics, the proportion of coal in total energy consumption remained above 55% in 2023. Nevertheless, high-intensity coal extraction will lead to safety production and eco-environmental issues, such as gas explosions, coal-rock mass bursts, water inrush accidents, water resources loss, and eco-environmental deterioration [2–4]. Roof water hazards are more prominent in the mine water disasters. The main reason is that water-conducting cracks penetrate the overlying aquifer [5,6], and underground water flows into the working sites through mining-induced cracks.

In this regard, researchers in the scientific community have conducted some research. Based on actual engineering cases, an empirical formula for the water-conducting fracture

zone (WCFZ) height is summarized [7]. Nevertheless, with the change in geological conditions, the empirical formula may not accurately predict the WCFZ height, and the applicability is relatively poor. As such, scholars have conducted in-depth research on the WCFZ development [7–9]. Limited by the surroundings, the microtremor survey and the opposing coil transient electromagnetic methods were applied to investigate the distribution of the water-conducting fracture passageways and further validated by the drilling [10]. Geophysical explorations and borehole investigation were adopted in the spatial distribution characteristics of WCFZ [11–14]. An approach based on the Brillouin optical time-domain reflectometry was proposed [15,16]. In addition, tracer tests were used to identify the water-conducting channels [17–19]. However, these methods not only consume time and economic cost but are also influenced by the operating circumstances. Considering that the WCFZ is affected by many factors, the weight of factors is identified by grey correlation, principal component analysis, and so on, and a multivariate regression model was established to predict its height [16,20–23]. Moreover, numerical simulation and physical material simulation were conducted to survey the fissure development law and its height [12,24–26]. The theoretical calculation of WCFZ was proposed by analyzing the ultimate deflection and free space height of overburden and tensile strain [27]. With the continuous promotion of artificial intelligence, machine learning has been gradually applied to various fields. Zhao and Zhu et al. [11,28] used different optimization algorithms to optimize the prediction ability of extreme learning machine models for predicting the WCFZ height. The genetic algorithm (GA) was employed to search for the optimal support vector regression model to improve the prediction accuracy [29]. An improved back propagation neural network model using GA was established to predict the WCFZ height [30]. A method to determine the development height based on multiple nonlinear regression models was optimized using the Entropy method after comparing it with random forest and support vector machine models [31].

Given the previous research, we select the primary factors affecting the WCFZ height and propose an improved back propagation neural network prediction model optimized by the differential evolution and grey wolf optimizer (DEGWO-BPNN). In addition, four comparison models are selected including the root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and Pearson determination coefficient (R^2) to assess the prediction performance. Lastly, the DEGWO-BPNN model is applied to the actual engineering case, and its prediction performance is better than the comparison models. As such, the improved BPNN model can predict the WCFZ height well and provide a valuable reference for mine safety operations.

2. Influencing Factors of the Height of WCFZ

Based on extensive theoretical and field research findings, some factors affecting the development height of WCFZ mainly include the following aspects:

(1) Mining height

Mining height is the only parameter contributing to the empirical formula in the ‘Code for Coal Pillar Setting and Mining’ jointly formulated by four national departments. It is the main factor affecting the height development of WCFZ. Some engineering cases show that with an increase in mining height, the range of the plastic zone in overlying strata will also increase accordingly; that is, the height of the caving zone and WCFZ will increase.

(2) Mining depth

The damaged degree and range of the surrounding rock after excavation are often affected by the stress of the rock mass near the excavation space. The original stress of rock mass includes gravity stress and tectonic stress. In general, the greater the mining depth, the greater the initial stress due to gravity stress, and the more serious damage degree of overlying rock after excavation will appear. Therefore, the development height of WCFZ is positively correlated with the mining depth.

(3) Panel width

Panel width is also one of the important factors affecting the development height of WCFZ. Overlying strata can be regarded as rock beams fixed at both ends. When the mining span of the working face is larger, the rock beams will bend downward under the gravity action, resulting in a greater development height of WCFZ. However, with an increase in panel width, the height of the fissure zone increases slowly and finally reaches a stable level and does not increase with the increase in panel width.

(4) Ratio of hard rock

The structure type and compressive strength of the combined rock strata also affect the development height of WCFZ. Under normal circumstances, the higher the strength of the overlying rock, the higher the development height of WCFZ. However, it is difficult to quantify the roof strata whole strength and the combination structure; therefore, we introduce a parameter ratio of hard rock b referring to the ratio of the accumulated thickness of hard rock in the mining influence range, which is 15 to 20 times of the mining thickness in most cases [32]. Thus, the empirical formula is as follows:

$$b = \frac{\sum h}{(15 \sim 20)M} \quad (1)$$

where b is the ratio of hard rock, M is the mining thickness, and $\sum h$ is the accumulated thickness of hard rock within the mining influence range.

(5) Coal seam dip

Due to the differences in the occurrence characteristics of coal seams, coal seams can be divided into nearly horizontal coal seams ($<8^\circ$), gently inclined coal seams ($8\text{--}25^\circ$), inclined coal seams ($25\text{--}45^\circ$), and sharply inclined coal seams ($>45^\circ$) according to the coal seam dip. Because the sliding state of rock strata after the formation of mining cracks will be affected by the inclination degree of rock strata, that is, when the inclination of coal seam changes greatly, there will be great differences in the development process, distribution pattern, and maximum height of WCFZ.

The descriptive information of the above-mentioned influencing factors is shown in Figure 1a,b.

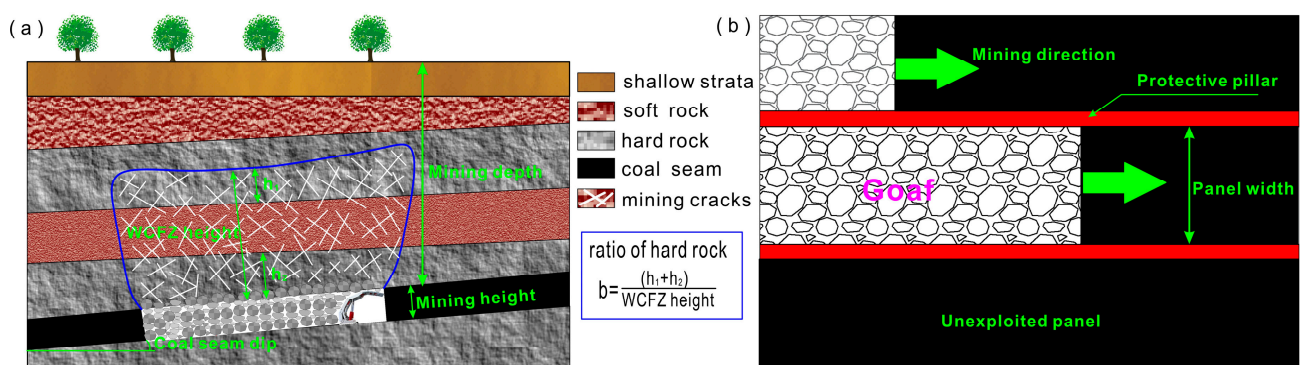


Figure 1. Underground mining section (a) and plan (b) schematic diagram.

Based on the previous studies, the five factors such as mining thickness, mining depth, panel width, the ratio of hard rock, and coal seam dip are selected as the main parameters for the prediction height of WCFZ. Through on-site investigation and reference to relevant literature, a total of 129 field-measured data sets of WCFZ and influence factors are collected, as shown in Figure 2. In total, 129 data sets are presented in detail in Appendix A.

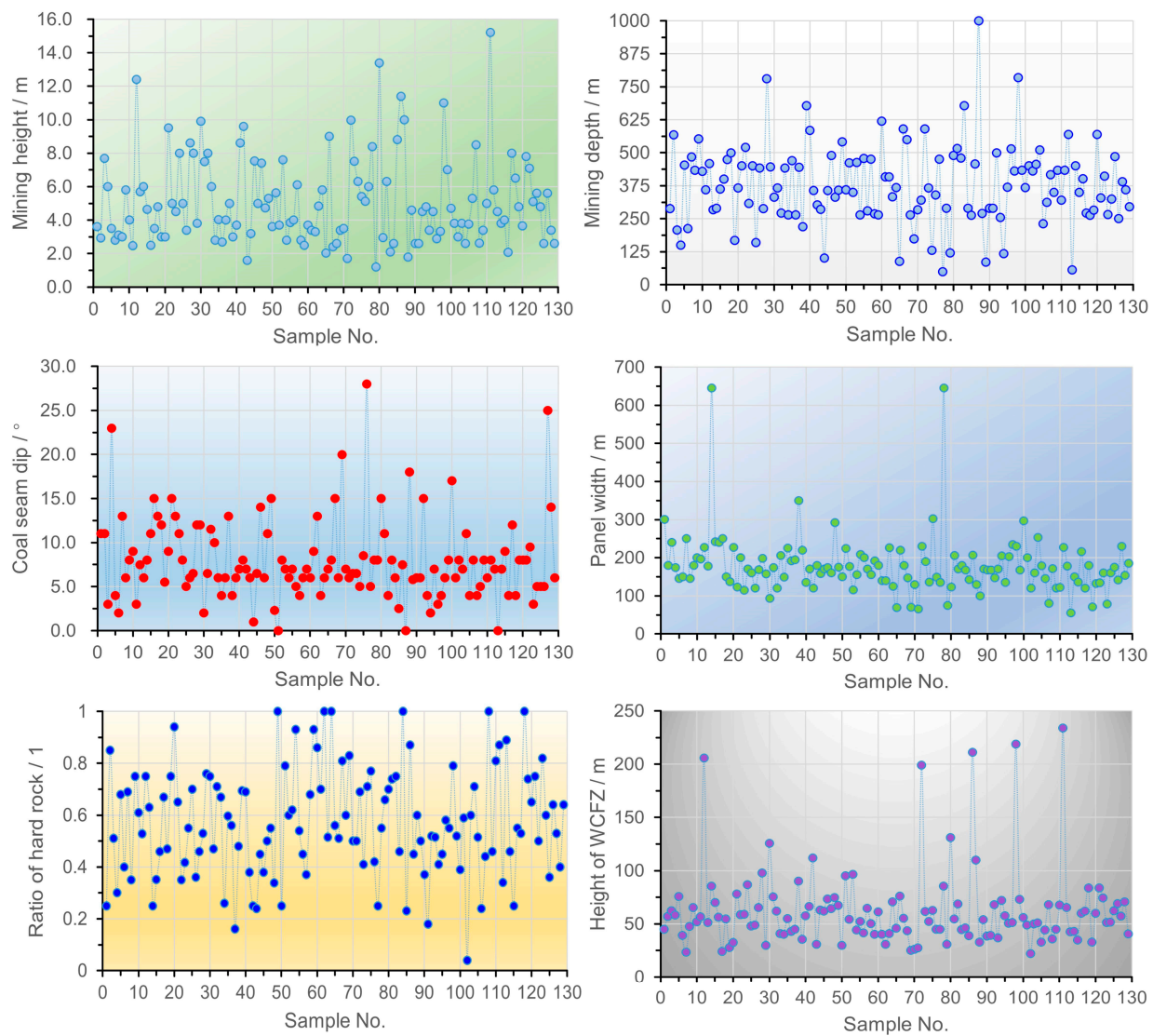


Figure 2. Primary factors and measured height of WCFZ.

3. Optimization Model and Evaluation Indexes

3.1. Back Propagation Neural Network

The back propagation neural network (BPNN) is a multi-layer forward and feedback neural network [33,34], which is composed of the input layer, hidden layers, and output layer. BPNN has unique advantages in dealing with complex nonlinear relationships under the influence of multiple factors with its multi-layer neuron connection and activation function. It continuously trains the samples through the back propagation algorithm to determine the deviation between the predicted output and the actual value. Once the deviation exceeds the expectation, the deviation signal will be propagated backward along the neural network to each network layer, the weight and bias of the neuron nodes will be updated according to the prediction error, and the iteration will be repeated until the expected goal is achieved. Figure 3 is the BPNN topology structure with multiple hidden layers. Although the nonlinear generalization ability of BPNN is strong, it takes a long time to search for the optimal solution by multiple iterative training, the convergence is poor, it is not easy to escape from the local extremum, and the prediction error is relatively large [35,36]. As such, the traditional BPNN prediction has great limitations in some fields.

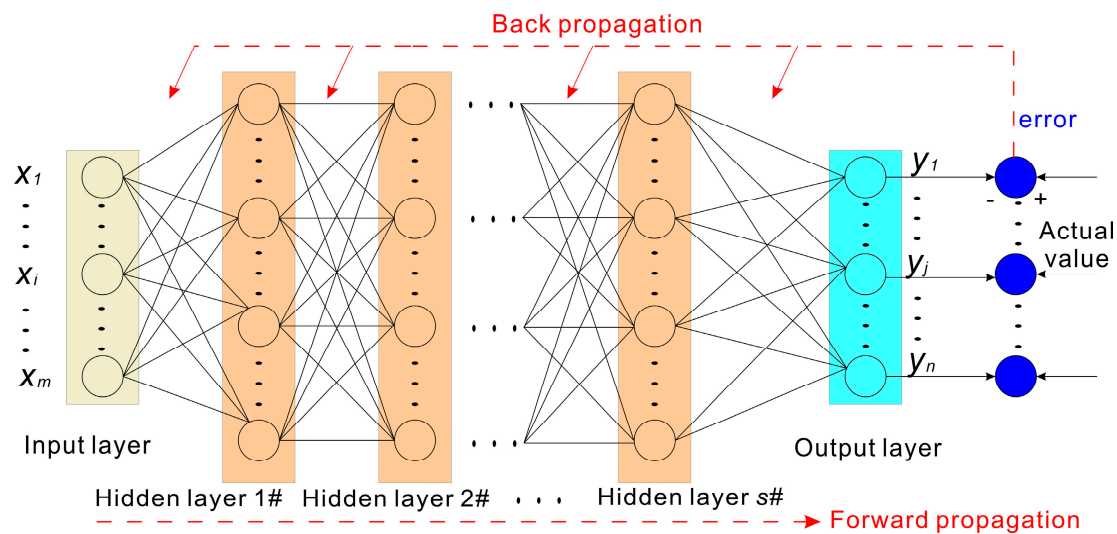


Figure 3. BPNN topology structure.

3.2. DEWGO Algorithm

3.2.1. Differential Evolutionary

R. Storn and K. Price [37] proposed the differential evolution (DE) algorithm to solve global optimization, which has been widely applied in engineering fields [38,39]. DE is a greedy-based search method. After randomly initializing the population, some better individuals are selected through the fitness function, and the selected individuals are subjected to mutation, crossover, and selection operations to generate a new population. The fitness function is applied again to select a new optimal individual and update the population. The iteration cycle is not terminated until the expected optimal is achieved. As such, the DE algorithm is utilized to search for the weight and bias of BPNN, which can improve the prediction accuracy of the model. The mutation, crossover, and selection operations of the algorithm are performed according to Equations (2)–(4).

$$v_i(g) = x_{r_1}(g) + F \times (x_{r_2}(g) - x_{r_3}(g)) \quad (2)$$

where r_1 , r_2 , and r_3 are different positive integers and are not equal to i representing the i -th individual in the evolution process, g is the evolution number, and F is the scaling factor, limited in $(0, 1.0)$.

$$u_{i,j}(g) = \begin{cases} v_{i,j}(g) & \text{if } \text{rand}(0, 1.0) \leq \text{crossover rate (CR)} \text{ or } j = j_{\text{rand}} \\ x_{i,j}(g) & \text{otherwise} \end{cases} \quad (3)$$

where $j = 1 \sim D$, j_{rand} is a random integer of $1 \sim D$, rand is a random number of $(0, 1.0)$, crossover rate (CR) is limited in $(0, 1.0)$, and $u_{i,j}(g)$ is the j -th gene of the i -th individual in the evolution number g .

$$x_i(g+1) = \begin{cases} u_i(g) & \text{if } f(u_i(g)) \leq f(x_i(g)) \\ x_i(g) & \text{otherwise} \end{cases} \quad (4)$$

In Equation (4), $x_i(g+1)$ is the target vector of the evolution algebra $(g+1)$, and i stands for the i -th individual in the evolution process.

3.2.2. Grey Wolf Optimization

Mirjalil et al. [40] first proposed a novel meta-heuristic named Grey Wolf Optimizer (GWO) in 2014, which was inspired by the hunting behaviour of grey wolves. The algorithm imitates the leadership structure and hunting strategy of grey wolves in nature. α , β , δ , and

ω are the four varieties of grey wolves that are applied to simulate the leadership structure. Furthermore, the primary steps of hunting, searching for prey, surrounding prey, and attacking prey are implemented to search for the best solution. In the GWO algorithm, α is considered the best agent, while the candidate agent of ω is less superior to the other three.

Grey wolves surround prey during the hunting process, and the surrounding behaviour is expressed by the mathematical model:

$$\begin{cases} D = \left| \vec{C} \times \vec{X}_p(t) - \vec{X}(t) \right| \\ \vec{X}(t+1) = \vec{X}_p(t) - \vec{A} \times \vec{D} \\ \vec{A} = 2\vec{a} \times \vec{r}_1 - \vec{a} \\ \vec{C} = 2 \cdot \vec{r}_2 \\ a = 2 \left(1 - \frac{t}{t_{\max}} \right) \end{cases} \quad (5)$$

where t indicates the current iteration; $\vec{A}$ and $\vec{C}$ are coefficient vectors; $\vec{X}_p(t)$ is the position vector of the prey; $\vec{X}(t)$ indicates the position vector of a grey wolf; component D of $\vec{D}$ is the distance between the grey wolf and the prey; $\vec{X}(t+1)$ is the updated position of a grey wolf; $\vec{a}$ is the vector representing the attack range of a grey wolf; component a of $\vec{a}$ is the convergence factor affecting the change of $\vec{A}$, ranging from 0 to 2.0; r_1, r_2 are random vectors in (0, 1.0).

During hunting, the position of the prey is estimated using the updating positions of α , β , and δ wolves:

$$\begin{cases} D_\alpha = \left| \vec{C}_1 \times \vec{X}_\alpha - \vec{X} \right|, D_\beta = \left| \vec{C}_2 \times \vec{X}_\beta - \vec{X} \right|, D_\delta = \left| \vec{C}_3 \times \vec{X}_\delta - \vec{X} \right| \\ \vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \times \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \times \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \times \vec{D}_\delta \\ \vec{X}(t+1) = (\vec{X}_1 + \vec{X}_2 + \vec{X}_3)/3 \end{cases} \quad (6)$$

where D_α, D_β , and D_δ are the approximate distances between the current grey wolves tending to α, β , and δ wolves, respectively; $\vec{D}_\alpha, \vec{D}_\beta$, and $\vec{D}_\delta$ are the distance vectors; $\vec{X}_\alpha, \vec{X}_\beta$, and $\vec{X}_\delta$ are the current positions of α, β and δ wolves, respectively. $\vec{X}_1, \vec{X}_2$, and $\vec{X}_3$ are the forward progress length and direction of ω wolf to α, β , and δ wolf, respectively, and $\vec{X}(t+1)$ is the updated position of ω wolf.

3.3. DEGWO-BPNN

3.3.1. Concept of DEGWO-BPNN

Because the grey wolf algorithm has the defect of premature stagnation, a hybrid differential evolution grey wolf optimizer algorithm (DEGWO) was proposed on account of the GWO algorithm. DE algorithm is applied to mutate the population, making GWO jump out of the search stagnation state, accelerating the convergence speed, and improving its performance. DE algorithm performs mutation, crossover, and selection operations on the population updated by the GWO algorithm to keep the diversity of the population. Using the powerful search ability of the DE algorithm, the α, β , and δ wolves are selected from the population position updated by DE, thus jumping out of the situation where the GWO algorithm falls into search stagnation. The optimal weight and threshold of BPNN can be searched in DEGWO, and the prediction performance and generalization ability of the BPNN model can be greatly improved.

3.3.2. Prediction Flow of DEGWO-BPNN Model

The process of the BPNN prediction model based on the DEGWO optimization algorithm is shown in Figure 4. Firstly, the collected data samples are classified into the training set and testing set. DE algorithm parameters are initialized to generate the grey wolf initial population. The fitness function is applied to calculate the best fitness of the α , β , and δ grey wolves. The position of the parent population is updated, and the mutation population and the offspring population are determined by the three basic operations of the DE algorithm. The fitness function is used again to select a new optimal individual and update the position of the population for the α , β , and δ grey wolves. Finally, the population position of α grey wolf is treated as the best position. The weight and threshold corresponding to the best position are the optimal weight and threshold. If the result satisfies the termination condition set before, the DEGWO algorithm ends the iteration operation; otherwise, it will be iterated again until the iteration reaches the maximum number. The optimal weight and threshold are transferred to the pre-set BPNN model. The training set data are continuously trained to determine the best training model. Then, the test set is used to test the prediction effect of the model. Once the deviation between the predicted result and the actual value is small, the training operation is completed when the accuracy requirement is met. If the desired outcome is not achieved during the training process, the training will continue until the maximum number of iterations is reached.

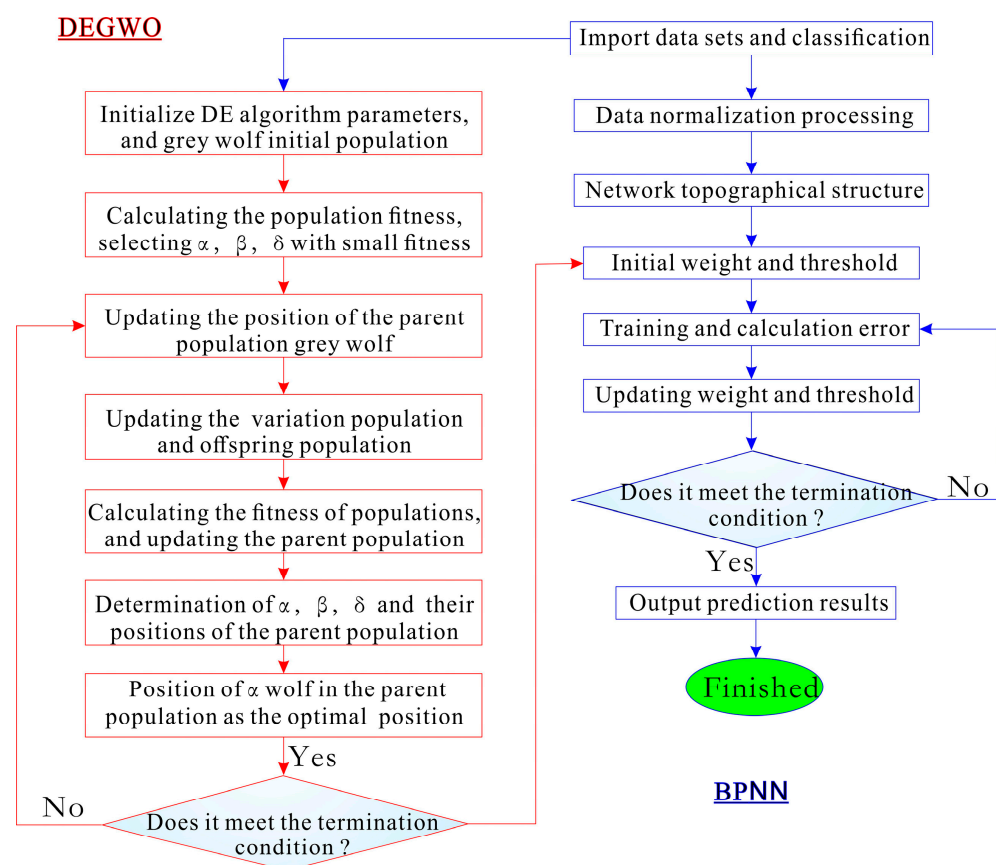


Figure 4. Flow chart of DEGWO-BPNN prediction.

3.4. Evaluation Indexes

In addition, we selected several evaluation indicators, including the root mean square error (RMSE), mean absolute error (MAE), mean absolute error percentage (MAPE), and

determination coefficient (R^2), to evaluate the prediction performance of the target model and the comparative models, and the evaluation indexes are calculated using Equation (7).

$$\left\{ \begin{array}{l} RMSE = \sqrt{\frac{\sum_i (y_i - \hat{y}_i)^2}{N}} \\ MAE = \frac{\sum_i |y_i - \hat{y}_i|}{N} \\ MAPE = \frac{\sum_i \left| \frac{y_i - \hat{y}_i}{y_i} \right|}{N} \times 100\% \\ R^2 = 1 - \frac{\sum_i (y_i - \bar{y}_i)^2}{\sum_i (y_i - \hat{y}_i)^2} \end{array} \right. \quad (7)$$

where y_i , $\hat{y}_i$, and $\bar{y}_i$ are the actual value, the prediction value, and the actual mean value; N is the number of data samples.

Moreover, the prediction accuracy of the models is calculated by $(1 - MAPE) \times 100\%$, when the MAPE value is determined using Equation (7).

4. Prediction Model of WCFZ Height Based on DEWGO-BPNN

4.1. Data Classification and Pre-Processing

In this study, the total data samples are divided into two categories, i.e., training set and testing set, using the ratio of 4:1; that is, 104 samples are used for the training network, and 25 samples are used as testing data. To eliminate the influence of the dimension scale of each characteristic index and the WCFZ height on the prediction precision, improve the training speed of the model, and ensure the prediction ability of the BPNN model, the input data of training database and testing database and output data of training database are standardized using the *mapminmax* () function before training. The range of the standardized data is $(-1.0, 1.0)$. Then, when the model outputs the prediction value of the testing samples, the reverse normalization method is applied to convert the prediction value into the WCFZ height with the unit.

4.2. Determination of DEWGO-BPNN Structure and Its Parameters

The prediction process of the model is finished in MATLAB 2023a environment. Since five characteristic factors are selected to predict the height of WCFZ, the number of input nodes N_{input} is 5, the number of output nodes N_{output} is 1, and the number of hidden layer nodes N_{hidden} can be determined using the following empirical formula [41].

$$N_{hidden} = \sqrt{(N_{input} + N_{output})} + c \quad (8)$$

where c is a positive integer ranging from 0 to 10.

Considering the convergence speed and accuracy of the neural network, the number of the hidden layer is set to 1, and the number of hidden layer nodes is set to 12. As such, the final topology number of the BPNN model is determined to be '5-12-1'. In addition, the 'tansig' function is considered as the activation function of the hidden layer, the 'purelin' function is the activation function of the output layer, and the Levenberg–Marquardt (*trainlm*) algorithm is used for training; the training number is 60, the learning rate is 0.01, and the minimum error of the training target is 0.00001.

According to the topological structure of the BPNN model, the dimensions D of the DEWGO and GWO are calculated by $D = N_{input} \times N_{hidden} + N_{hidden} \times N_{output} + N_{hidden} + N_{output}$, and the calculation result of D is 85. In the DE algorithm, the scaling factor F ranges from 0.2 to 0.8, and CR is 0.2. The number of grey wolf population is 10, and the maximum

number of iterations is 15. The upper and lower limits of the independent variable are -3 and 3 .

4.3. Training and Prediction Results

Through the hybrid DEGWO algorithm, the optimal weight and threshold are found and exported into the BPNN model. The improved prediction model first iteratively trains 104 samples to determine the best training model. The relationship between the prediction height of WCFZ simulated by the training model and the actual value is shown in Figure 5a. The deviation between the predicted value and the actual value of the training samples is relatively smaller, and the height of WCFZ can be predicted more accurately. In terms of the evaluation indexes reflecting the performance of the training model, the MAE, RMSE, MAPE, and R^2 are 2.3952, 3.4674, 5.3148%, and 0.99077, respectively. The prediction accuracy is 94.6852%. Moreover, 25 testing samples further verify the reliability of the model as shown in Figure 5b. The predicted value of the testing samples fluctuates around the actual value, and the deviation is relatively smaller.

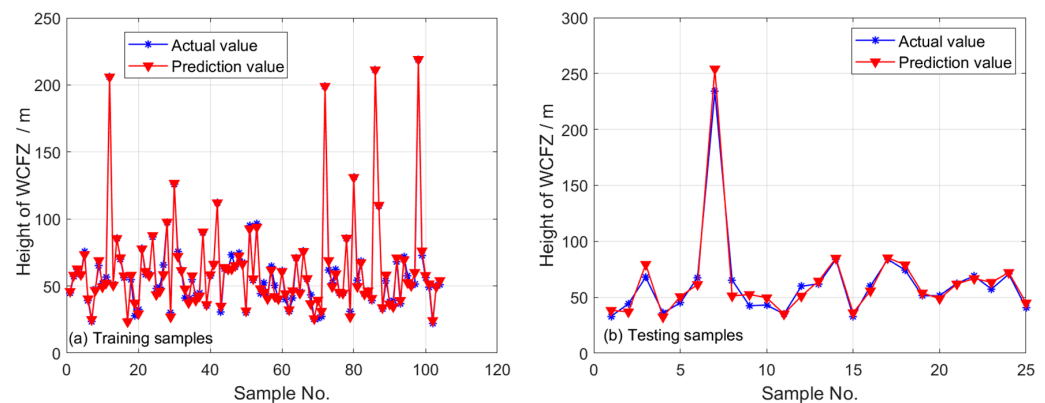


Figure 5. Comparison between the actual and prediction values for training and testing data.

In addition, the fitness value can also determine whether the prediction results of the model reach the expected accuracy. RMSE is treated as a fitness value in this study, and the lower the RMSE value of the model, the better the prediction performance of the model. In Figure 6a, when the iteration number of the DEGWO algorithm is 10, the fitness value decreases to less than 6.0 and then tends to be stable. In the improved BPNN model, MSE can be used as a quantitative reflection of training performance. When the maximum number of training rounds is reached, the optimal training performance value is 1.2392×10^{-3} as shown in Figure 6b.

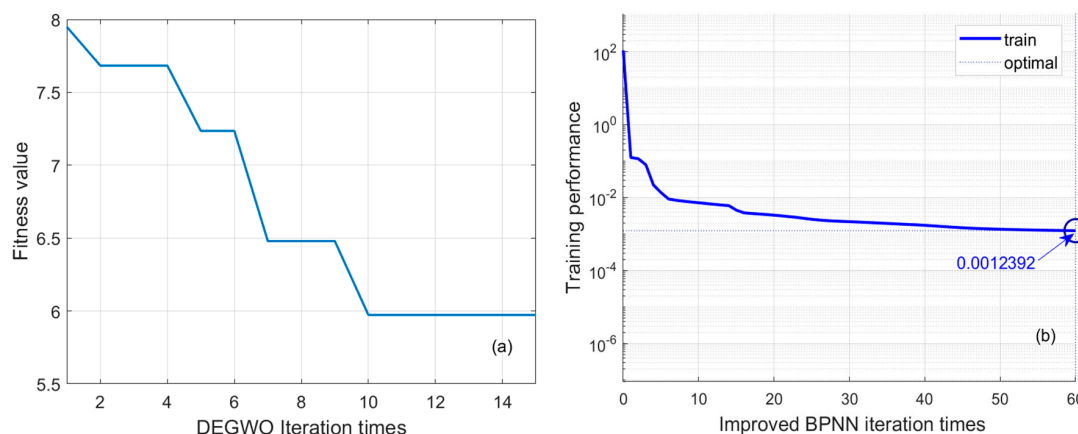


Figure 6. DEGWO-BPNN model error iteration curve. (a) is fitness value of DEGWO algorithm iteration; (b) is training performance of improved BPNN model.

4.4. Comparative Analysis

To highlight the superiority of DEGWO-BPNN prediction performance, we compare the prediction performance of other methods, such as ‘Mining Code’, multiple linear regression (MLR), BPNN, and GWO-BPNN. ‘Building, water, railway and main roadway pillar setting and coal mining code’ is referred to as ‘Mining Code’, which was released by four National Administrations, including the State Administration of Safety Supervision, the National Coal Mine Safety Administration, the National Energy Administration, and the National Railway Administration of the People’s Republic of China in 2007. MAE, MAPE, RMSE, and R^2 are used to evaluate the prediction performance of these models. The prediction results of five models on 25 testing samples are shown in Table 1.

Table 1. Evaluation indicators and prediction accuracy of five models.

Prediction Models	MAE	MAPE	RMSE	R^2	Prediction Accuracy
Mining Code	27.69	40.63%	40.38	0.2332	59.37%
MLR	13.64	22.55%	19.06	0.7631	77.45%
BPNN	11.39	18.68%	16.06	0.8211	81.32%
GWO-BPNN	8.53	15.41%	11.14	0.9625	84.59%
DEGWO-BPNN	5.44	9.30%	7.089	0.9779	90.70%

It can be seen from Table 1 that the BPNN optimized by the DEGWO hybrid algorithm has significantly improved the prediction accuracy compared with the prediction results of the BPNN model. To be specific, the prediction accuracy of the DEGWO-BPNN model is close to 10% greater than that of the BPNN model, while the prediction accuracy of the GWO-BPNN model is between the DEGWO-BPNN model and the BPNN model. In five of the prediction models, the prediction performance of WCFZ height calculated by ‘Mining Code’ is the worst, followed by MLR. Their prediction accuracies are 59.37% and 77.45%, respectively.

Furthermore, the quantitative evaluation indexes also show a certain change characteristic; MAE, RMSE, and MAPE show a downward trend from the conventional ‘Mining Code’ prediction method to DEGWO-BPNN, while R^2 and prediction precision increase, as shown in Figure 7. Using the machine learning method, such as BPNN and improved BPNN, the model prediction performance is effectively improved. In particular, when the BPNN is optimized, the expected values of each evaluation index are ideal. The prediction accuracy of the GWO-BPNN model and DEGWO-BPNN model is better than the other three models. To obtain the optimal prediction performance, differential evolution is introduced to optimize the GWO algorithm for the search for the best weights and threshold in the BPNN model. Compared with the GWO-BPNN model, the prediction accuracy of the DEGWO-BPNN model is improved by 6.11%. MAE, MAPE, RMSE, and R^2 of the DEGWO-BPNN model are also better than those of the GWO-BPNN model.

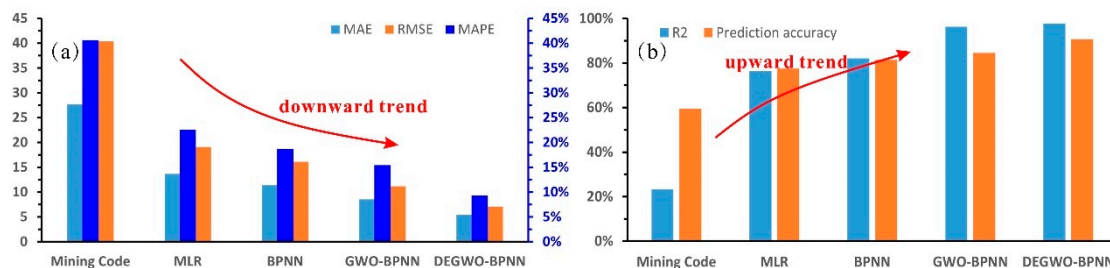


Figure 7. Comparison of evaluation indicators in five prediction models. (a) is the comparison of MAE, RMSE and MAPE in five prediction models; (b) is the comparison of R^2 and Prediction accuracy in five prediction models.

5. Engineering Application

Dananhu No.7 Coal Mine belongs to Hami Energy Development Co., Ltd., China Coal Group. It is located in the Dananhu mining district of Tuha Coalfield, 40 km away from Hami Urban. With an area of 86.37 km², the designed production capacity is 12.0 Mt/a. No.1~No.5 mining areas are designed in the coal mine, of which the first mining area is the No.1 mining area.

The 11601 panel, the first mining panel, is located in the No.1 mining area. The length and width of the panel are 1900 m and 220 m, and the average dip angle of the coal seam is 5.0°. The fully mechanized mining technology with full mining height is adopted, and the mining height is 3.20 m. The ground elevation of the area where the panel is located ranges from +546 m~+550 m, and the elevation of the mining coal ranges from +250 m~+342 m. The exploration of WCFZ height was carried out on the surface of the 11601 panel in October 2023, and an exploration borehole named DS1 was constructed. The relevant parameters and measured results of WCFZ height are listed in Table 2.

Table 2. The relevant parameters and measured height of WCFZ.

Borehole ID	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock	Measured Height of WCFZ/m
DS1	3.20	173.13	5.0	220	0.49	52.50

The relevant parameters of WCFZ in Table 2 are imported into the prediction models to determine the predicted value of the WCFZ height using different prediction models, as shown in Table 3. After comparing the prediction value with the measured value, it is found that the prediction error of the DEGWO-BPNN model is lower than that of the comparison models, the absolute and relative errors are 0.53 m and 1.01% or so, and the prediction accuracy is higher. So, the hybrid optimization algorithm of the differential evolution and grey wolf can improve the performance of the model prediction, compared with the traditional neural network algorithm and other statistical methods.

Table 3. Comparison of prediction models for WCFZ in the 11601 panel.

Prediction Models	Prediction Height/m	Absolute Error/m	Relative Error/%
Mining Code	36.70	15.80	30.10
MLR	38.64	13.86	26.40
BPNN	44.87	7.63	14.53
GWO-BPNN	57.44	4.94	9.41
DEGWO-BPNN	53.03	0.53	1.01

6. Conclusions

In this study, we consider the advantages of the differential evolution and the grey wolf optimization, and a hybrid optimization algorithm of DEGWO is proposed. Through the powerful search ability of DEGWO, the optimal weight and threshold of BPNN are extracted to improve the prediction accuracy. The prediction performance of DEGWO-BPNN is discussed by taking the development height of WCFZ threatening the mine safety as the prediction object and compared with other prediction models using several evaluation indexes. The primary conclusions are made as follows:

(1) Based on systematic analysis, five main factors affecting the height development of WCFZ are determined, namely mining height, mining depth, coal seam dip, panel width, and ratio of hard rock. The topology structure of the DEGWO-BPNN model is preliminarily determined as ‘5-12-1’.

(2) The prediction model is preliminarily identified by training 104 samples. The deviation between the prediction value and the actual value of the training sample is smaller with an average error of 2.39. Testing samples further validate the reliability of

the prediction model through four evaluation indexes consisting of MAE, RMSE, MAPE, and R^2 . Their values are 2.3952, 3.4674, 5.3148%, and 0.99077, respectively. The prediction accuracy of the model is 94.6852%.

(3) ‘Mining Code’, MLR, BPNN, and GWO-BPNN are considered as the comparison models. The comparative analysis shows that the prediction performance of the WCFZ height calculated by ‘Mining Code’ is the worst, followed by MLR, while the prediction accuracy of the DEGWO-BPNN model is the best. Compared with the GWO-BPNN model, the prediction accuracy of the DEGWO-BPNN model is improved by 6.11%. It outperforms other algorithms and statistical approaches.

(4) BPNN optimized by the DEGWO algorithm is applied to predict the WCFZ height of the 11601 panel in the Dananhu No.7 Coal Mine. The prediction error of the DEGWO-BPNN model is lower compared with other prediction models. The relative error is 4.53%, and the prediction precision is higher.

As such, the DEGWO-BPNN model can be well applied to the prediction of WCFZ height. This method is suitable for coal mines with different regional geological conditions. It can provide a valuable reference for mine safety production because of its wider application range and higher prediction performance.

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Abbreviations

The following abbreviations are used in this manuscript:

BPNN	Back propagation neural network
DE	Differential evolution
GWO	Grey wolf optimizer
DEGWO	Differential evolution and grey wolf optimizer
WCFZ	Water-conducting fracture zone
MLR	Multiple linear regression
RMSE	Root mean square error
MAE	Mean absolute error
MAPE	Mean absolute percentage error
R^2	Pearson determination coefficient
B	Ratio of hard rock
CR	Crossover rate
Mining Code	Building, water, railway, and main roadway coal pillar setting and coal mining code

Appendix A. 129 Sample Data of Evaluation Indexes and WCFZ Height

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/ $^{\circ}$	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
1	Qianyingzi coal mine	3.6	288	11	301	0.25	45
2	Jining No.2 coal mine 1301 panel	2.94	568.4	11	180	0.85	57
3	Pingsuo coal mine	7.69	207	3	240	0.51	62.3
4	Hebi No.8 coal mine 11033 panel	6	150	23	174	0.3	58.4
5	Pansan coal mine	3.5	453	4	145	0.68	75.8
6	Pingquan coal mine	2.8	213	2	150	0.4	39.2
7	Gubei coal mine 1242 panel	3.1	484	13	250	0.69	23.51
8	Panyi coal mine	3	434	6	145	0.35	47.6
9	Panyi coal mine 2622 panel	5.8	553	8	180	0.75	65.3
10	Zhangji coal mine 1215 panel	4	429	9	200	0.61	52
11	Malan coal mine 12511 panel	2.47	359	3	196	0.528	56.71
12	Taiping coal mine N1S1 panel	12.4	458.9	7.5	227	0.75	205.9
13	Xinlong coal mine 2303 panel	5.7	283.9	6	178	0.63	51.4
14	Xinji coal mine	6	290	8	645	0.25	85.6
15	Xiegou coal mine 18101 panel	4.65	362	11	242	0.351	70.2
16	Longtan coal mine	2.5	400	15	240	0.46	56.37
17	Gubei coal mine 1232 panel	3.5	474	13	250	0.67	24.09
18	Xieqiao coal mine 11213 panel	4.8	500	12	150	0.47	54.79
19	Baishan coal mine 664 panel	3	168	5.5	137	0.75	27.8
20	Baodian coal mine	3	367	9	227	0.94	32.5
21	Zhuxianzhuang coal mine	9.5	450	15	123	0.65	78
22	Xieqiao coal mine	5	520	13	200	0.35	58.5
23	Zhenchengdi coal mine 28103 panel	4.5	308	11	115	0.417	59
24	Xinlong coal mine	8	450	8	170	0.55	86.8
25	Daliuta coal mine 12610 panel	5	160	5	160	0.7	48

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
26	Panyi coal mine	3.4	442	6	120	0.36	48.9
27	Baodian coal mine 1316 panel	8.61	288	6.5	169	0.46	65.5
28	Tianchen coal mine	8	781	12	198	0.53	97.7
29	Zhangji coal mine 17116 panel	3.8	446	12	157	0.76	30
30	Xiagou coal mine ZF2801 panel	9.9	332	2	93	0.75	125.8
31	Baodian coal mine 1314 panel	7.5	367	6.5	174	0.47	75.5
32	Yangcun coal mine 301 panel	8	272	11.5	120	0.71	62
33	Zhangji coal mine 1611 panel	6	442	10	206	0.67	41
34	Xinlong coal mine 2306 panel	2.8	264.5	6	149	0.26	40.35
35	Malan coal mine 18301 panel	4.03	470	4	225	0.596	54.96
36	Xinlong coal mine 2300 panel	2.7	265	6	192	0.56	42.81
37	Zhangji coal mine	4	445	13	195	0.16	45
38	Yushuwan coal mine 20102 panel	5	220.1	4	350	0.48	90
39	Guandi coal mine 22611 panel	2.99	679	6	220	0.695	35.5
40	Zhangji coal mine 1221 panel	3.7	584	7	135	0.69	57.5
41	Baodian coal mine	8.6	357	8	170	0.38	66.5
42	Xiexin coal mine 1703-1 panel	9.6	302	7	120	0.25	112
43	Yangcun coal mine 3701 panel	1.6	285	6	180	0.24	30.8
44	Wulanmulun No.3 coal mine	3.2	101.1	1	158	0.45	63
45	Baodian coal mine 1316 panel	7.53	357	6.5	170	0.38	61.9
46	Xieqiao coal mine	5	489	14	174	0.5	73.3
47	Xinglongzhuang coal mine 4314	7.4	331	6	160	0.55	64.25
48	Xiegou coal mine 18102 panel	4.72	358	11	292	0.339	74.8
49	Nantun coal mine 9301 panel	5.3	542	15	175	1	67.5

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
50	Beizhao coal mine H2101 panel	3.6	359	2.3	150	0.25	30
51	Dongtan coal mine	5.62	462	0	224	0.79	95.1
52	Taoyuan coal mine 1031 panel	3.7	350	8	177	0.6	54.3
53	Tingnan coal mine 106 panel	7.6	463	7	116	0.62	96.4
54	Xinglongzhuang coal mine 2306 panel	2.8	264.5	6	156	0.93	44.34
55	Zhangji coal mine	3.85	478	7	209	0.54	52.2
56	Shenjiawan coal mine 2666 panel	4	280	5	200	0.45	41.4
57	Jining No.3 coal mine 1301 panel	6.1	475	4	170	0.37	64.6
58	Xinglongzhuang coal mine 2308 panel	2.8	269	6	156	0.68	50.34
59	Xinlong coal mine	2.5	265	7	192	0.93	40.21
60	Guotun coal mine 1310 panel	3.7	620	6	180	0.86	61.3
61	Pansan coal mine 1221 panel	3.4	409	9	140	0.7	40.2
62	Pansan coal mine 1211 panel	3.3	408	13	140	1	30.9
63	Dongqu coal mine 28806 panel	4.83	333	4	226	0.515	41
64	Nantun coal mine 6310 panel	5.8	368	6	125	1	70.7
65	Liuhualing coal mine	2.03	89	7	69	0.56	45.86
66	Baodian coal mine	9	590	8	220	0.51	76
67	Qidong coal mine 3241 panel	2.4	550	15	180	0.81	55.32
68	Xinglongzhuang coal mine 2306 panel	2.6	265	6	147	0.6	43.43
69	Fangezhuang coal mine	3.38	173	20	70	0.83	25.3
70	Luling coal mine	3.5	284	7	130	0.5	26
71	Yangzhuang coal mine	1.7	320	6	65	0.5	27.5
72	Xiaokang coal mine S2S7 panel	9.97	590	6.5	230	0.69	199

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
73	Baodian coal mine 5306 panel	7.52	367	6.5	190	0.41	61.77
74	Chaili coal mine 301 panel	6.3	130	5	136	0.71	52.2
75	Hongliu coal mine 1211 panel	5.4	340.6	8.5	302	0.77	62.53
76	Xinji No.2 coal mine	5.13	475	28	149	0.42	45
77	Daliuta coal mine 1203 panel	6	49	5	135	0.25	45
78	Xinji coal mine	8.4	290	8	645	0.55	85.6
79	Zhaopo coal mine	1.2	120	8	75	0.66	31
80	Zhuxianzhuang coal mine	13.4	490	15	123	0.7	131
81	Jining No.2 coal mine 2301 panel	2.95	516	11	206	0.74	54.5
82	Jining No.3 coal mine	6.3	480	4	170	0.75	68.6
83	Shengda coal mine 21010 panel	2.1	679	8	180	0.46	44.54
84	Xinglongzhuang coal mine 2302 panel	2.6	290	6	168	1	46.22
85	Taiping coal mine 8301 panel	8.8	262.8	2.5	143	0.23	39
86	Taiping coal mine N1N4 panel	11.4	458	7.5	207	0.87	211.2
87	Bingchang coal mine	10	1000	0	130	0.45	110
88	Pan'er coal mine 1102 panel	1.8	270	18	100	0.6	33
89	Nantun coal mine	4.6	86.1	5.8	170	0.5	53.9
90	Xinglongzhuang coal mine 2302 panel	2.6	290	6	168	0.37	38.41
91	Xinglongzhuang coal mine 2302 panel	2.6	290	6	168	0.18	39.14
92	Xieqiao coal mine	4.5	499	15	147	0.52	67.9
93	Dongqu coal mine 28206 panel	4.79	255	4	170	0.515	36.75
94	Panxie coal mine C131 panel	3.4	117	2	205	0.41	72
95	Zhangji coal mine	4.5	370	7	135	0.45	57.5

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
96	Dijing coal mine 1141 panel	2.88	515	3	203	0.58	50.7
97	Tunlan coal mine 28120 panel	3.33	431	4	235	0.55	51.25
98	Taiping coal mine S2S7 panel	11	784	6	230	0.79	219
99	Xinlongzhuang coal mine 5306 panel	7	433	8	168	0.52	72.97
100	Renlou coal mine	4.7	368	17	297	0.39	56
101	Zhangji coal mine 1212 panel	3.8	450	6	200	0.59	49.1
102	Panyi coal mine	3	431	8	120	0.04	22
103	Pansan coal mine 1622 panel	3.8	456	7	160	0.6	50
104	Dijing coal mine 1262 panel	2.6	510	11	253	0.71	51
105	Dongqu coal mine 18311 panel	3.77	231	4	179	0.515	33
106	Xinlongzhuang coal mine	5.3	312	8	145.7	0.24	44.2
107	Baodian coal mine 13013 panel	8.5	417	4	80	0.44	68
108	Fangezhuang coal mine 3553S panel	2.62	350	5	171	1	35.95
109	Panyi coal mine	3.4	434	8	120	0.46	45
110	Nantun coal mine	5	320	6	122	0.81	67.7
111	Taiping coal mine N1S2 panel	15.2	433.9	8	227	0.87	234
112	Panyi coal mine	5.8	570	7	178	0.34	65.3
113	Bulianta coal mine	4.5	56	0	55	0.89	42.5
114	Pansan coal mine 1612 panel	3.8	451	7	150	0.46	43
115	Liangjia coal mine 1206 panel	4	350	9	136	0.25	35
116	Malan coal mine 10702 panel	2.08	402	4	216	0.55	59.87
117	Yangcun coal mine	8	272	12	120	0.53	62
118	unknown coal mine	6.5	263	4	180	1	83.9
119	Linnancang coal mine 1221 panel	4.8	282	8	71	0.74	33
120	Pansan coal mine	3.65	569	8	132	0.65	60.1

Sample No.	Coal Mine	Mining Height/m	Mining Depth/m	Coal Seam Dip/°	Panel Width/m	Ratio of Hard Rock/1.0	WCFZ Height/m
121	Xinji No.1 coal mine 1303 panel	7.8	329	8	134	0.75	83.9
122	Xinglongzhuang coal mine 5306 panel	7.1	412	9.5	160	0.5	74.4
123	Xuchang coal mine	5.1	266	3	78	0.82	51.3
124	Xinlongzhuang coal mine 4321 panel	5.6	325	5	160	0.6	51.5
125	Nantun coal mine	4.8	485	5	175	0.36	62.5
126	Lvshuidong coal mine	2.6	250	5	142	0.64	68.98
127	Kailuan linxi coal mine	5.6	391	25	230	0.53	57.3
128	Pansan coal mine 1711 panel	3.4	360	14	154	0.4	70.7
129	Xinglongzhuang coal mine 2301 panel	2.6	295	6	185	0.64	40.5

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