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Mining Technology Evaluation for Steep Coal Seams Based on a GA-BP Neural Network

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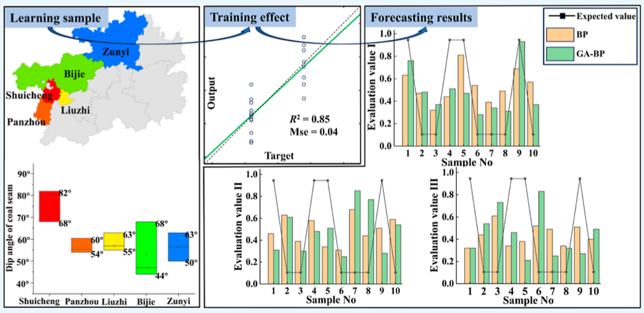
ABSTRACT: Many mines in Guizhou Province are in urgent need of renovation to ensure harmonious operation and prolong their lifespan. The key to successful renovation lies in the prudent selection of the appropriate mining technologies. Therefore, a comprehensive investigation was conducted on steep coal mines in Guizhou Province, and a comprehensive evaluation framework was established. Spearman correlation analysis was performed on various factors, selecting geological conditions and working face parameters with high correlation as the input variables and mining methods as the output variables. The optimal values of each hyperparameter were determined through orthogonal experiments, and the neural network structure was confirmed to be "17-9-3".



Five variants of backpropagation (BP) algorithms were meticulously tested, and a genetic algorithm optimizing the BP neural network (GA-BP) was further assessed to improve the model's prediction accuracy. The accuracy of the model was evaluated via the coefficient of determination (R^2) and mean squared error (MSE). The research results indicated that the variable step−size algorithm with a momentum term (VSS + MT) was the optimal algorithm for the BP neural network. Additionally, the MSE values of the artificial neural network and GA-BP neural network in the testing phase were 0.06 and 0.04, with prediction success rates of 70 and 90%, respectively, and R^2 values of 0.79 and 0.85, respectively. Thus, the GA-BP neural network demonstrated superior performance. Finally, industrial application of the model was conducted on a working face in the Zhong-Yu coal mine. The evaluation index for the working face was "0.847, 0.09, 0.111", suggesting that fully mechanized mining should be adopted. The evaluation results were consistent with the current production status of the mine, verifying the reliability of the model in practical applications.

1. INTRODUCTION

Coal seams exhibiting an inclination angle surpassing 45° are commonly referred to as steep coal seams.[1] Although these coal seams are ample and account for roughly 17% of the total coal reserves in China,[2] their yearly output represents a relatively meager fraction of the national total coal production, estimated to be between 8 and 10%.[3,4] Despite the presence of abundant steep coal resources in the Guizhou mining region, challenges, such as inadequate geological conditions and suboptimal selection of mining technologies, have led to a marked imbalance between coal storage and mining operations. The implementation of appropriate mining technologies is crucial for designing and planning the mining face related to steep coal seams and can substantially impact the reduction of cost per ton of coal and optimization of labor organization. Notably, multiple coal mine working faces in Guizhou are currently under suspension and renovation. The selection of suitable coal mining techniques is pivotal in determining the effectiveness of the renovation.

Scholars from various countries have conducted extensive research on the evaluation of mining processes and methods. Zhao et al.[5] developed a comprehensive optimization system for selecting a thick residual coal remining method, named the fuzzy analytic network process. This approach was based on fuzzy comprehensive evaluation and ANP, addressing issues such as fuzziness and subjectivity. Wang et al.[6] proposed a method that combined Monte Carlo simulation with the traditional analytic hierarchy process (AHP) to optimize decision making for selecting the best thin coal seam longwall mining method. These authors considered factors such as economics, technology, and ergonomics. Chander et al.[7] developed an improved AHP and VIKOR method to select the optimal mining method for bauxite ore, demonstrating that conventional mining was the most suitable method for this type of ore. Iphar and Alpay[8] developed

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a mobile application for selecting underground mining methods using multicriteria decision-making methods, such as TOPSIS, VIKOR, ELECTRE, FMADM, and PROMETHEE. Dogan[9] proposed a fuzzy multiple-criteria decision-making approach based on spherical fuzzy AHP for selecting the appropriate mining technology under uncertain and ambiguous conditions. Although concise and practical, the above methods suffer from shortcomings, such as insufficient quantitative data and difficulty in determining weights when there are too many indicators. Furthermore, weight determination is dependent on expert experience, rendering the reliability of these methodologies questionable.

In 1959, Arthur Samuel proposed the idea of machine learning for the first time.[10] This method can learn appropriate and effective characteristics from large amounts of complex data.[11−13] Since its introduction, machine learning has solved many complex prediction problems in mining, such as drilling fluid lost-circulation,[14] coalbed methane production,[15] coal mining,[16] nuclear magnetic resonance porosity,[17] shale brittleness,[18] etc.

Artificial neural networks (ANNs), as a rapidly evolving machine learning method, have emerged as pivotal tools for addressing complex problems across various scientific domains.[12] Among sundry ANN types, the backpropagation (BP) neural network represents a frequently employed and efficacious method.[19] BP neural networks possess the ability to learn nonlinear correlations between input and output variables using weight adjustments predicated upon a prescribed collection of training data.[20] Despite their ubiquity, BP neural networks are susceptible to converging toward local minima, and their training can be arduous and protracted.[21]

To mitigate these concerns, an adapted methodology was devised, referred to as the genetic algorithm-based BP neural network (GA-BP).[22] GA-BP fuses the BP algorithm with the global search proficiency of genetic algorithms, which leads to more expeditious and efficient training, surmounting the local minimum problem and converging toward a more optimal solution compared to traditional BP neural networks. Furthermore, the GA-BP network showcases superior resistance to noise and improved generalization capacity because of its exceptional global optimization capability. Therefore, GA-BP neural networks are progressively gaining popularity in diverse applications such as pattern recognition, prediction, and classification.

In recent years, a plethora of mining engineering problems have been resolved through the application of ANNs. Ozyurt et al.[23] developed six different ANN models and investigated the applicability of ANNs and game theory in the development of an underground mining method selection model. Yu and Ren[24] devised a GA-BP network image recognition model to contrast and choose multiple approaches for production blasting design, providing a quantitative basis for the rational selection of production blasting design parameters. Xu and Zhao[25] established a landslide stability analysis and prediction technique based on a GA-BP model, concluding that the GA-BP model algorithm was more accurate and had faster convergence than the BP model. Tan et al.[26] optimized a BP neural network with a genetic algorithm and inverted the position and intensity of gas explosion sources in roadways through gas explosion experiments and simulated overpressure data. Compared with the actual results, the model accurately determined the location of the explosion source and had a high reference value. Shan et al.[27] created an MIV-GA-BP fusion model for forecasting the stability of cross-section coal columns and applied the prediction model to verify its effectiveness in two field cases.

In summary, GA-BP neural networks have been widely applied in mining engineering-related problems. However, research on applying the GA-BP neural network to mining method selection and mining process evaluation is currently scarce. Therefore, the application of the GA-BP neural network to address mining method selection and mining process evaluation is the main focus of this article.

2. ARTIFICIAL NEURAL NETWORKS

2.1. BP Neural Network. The BP neural network is a complex feed-forward network that operates on the fundamental principle of error BP and gradient descent of weight. It comprises three distinct layers, namely, the input, hidden, and output layers, each of which contains several independent nodes or neurons. These neurons interact through the application of weights.[28,29] Notably, neurons in one layer can transmit signals only to neurons in the following layer via the neurons in the previous layer. The BP neural network structure is depicted in Figure 1.

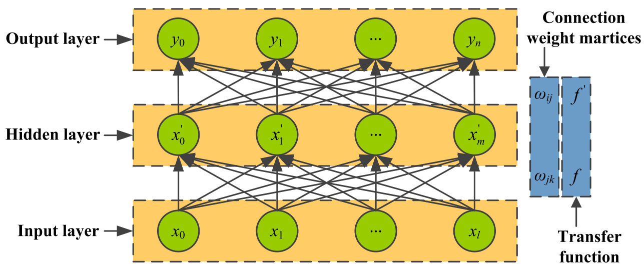

Figure 1. BP neural network structure.

The training procedure of the BP neural network comprises two key phases: forward signal propagation and backward error propagation. During the forward propagation phase, data from the input layer are conveyed to the hidden layer through weighted summation, followed by processing in the hidden layer and transmission to the output layer. If the output value of the output layer does not satisfy the error requirement, then backward propagation of errors is initiated. This phase includes transmitting the error from the output layer to the hidden layer in a particular form and then distributing it to the nodes in the input layer. Using forward propagation of signals and backward propagation of errors, the actual output value of the BP neural network gradually approaches the expected value. The iteration ends when the output value of the output layer satisfies the error requirement or a particular number of iterations have been accomplished.

Owing to the constant step size employed in conventional BP algorithms, the process of updating network weights may result in issues such as sluggish convergence and a high number of training iterations. To overcome these difficulties, enhanced BP algorithms derived from the standard BP model have been developed, which are mainly classified into the following categories:[30]

1. The variable step−size algorithm (VSS)

$$\omega_{ij}(n_0 + 1) = \omega_{ij}(n_0) + \eta(n_0)d(n_0) \tag{1}$$

2. The inclusion of a momentum term (MT) algorithm

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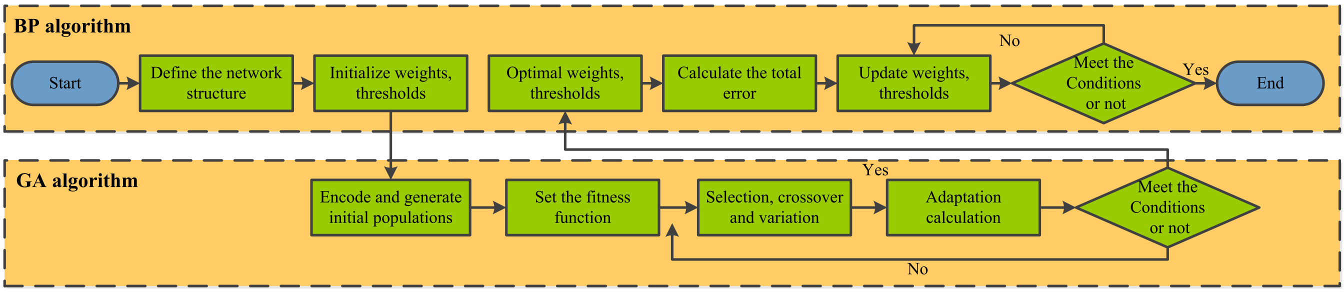

Figure 2. GA-BP neural network structure.

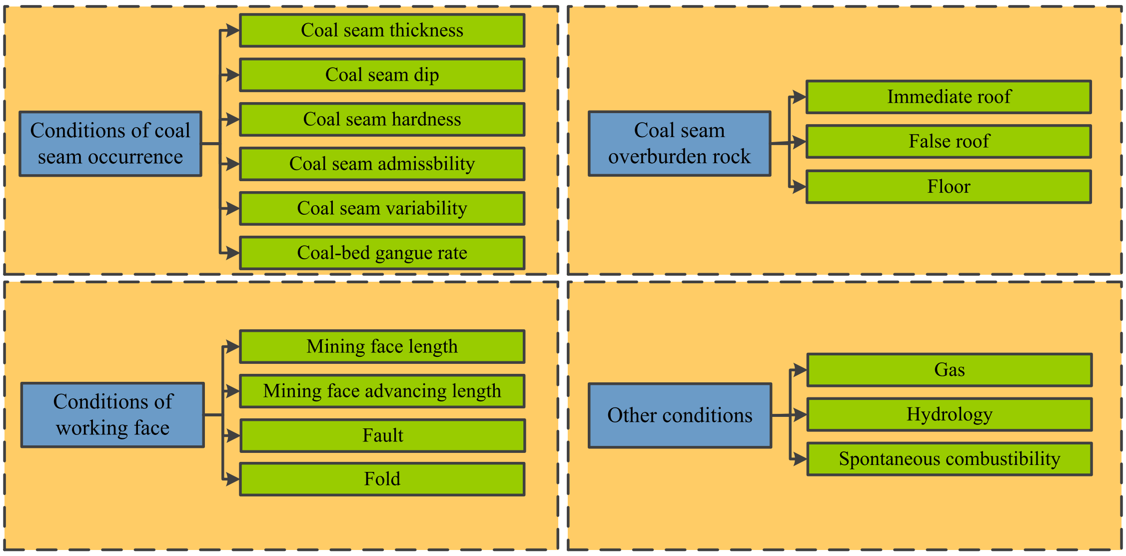

Figure 3. Evaluation index system for steep coal seam mining methods.

$$\omega_{ij}(n_0 + 1) = \omega_{ij}(n_0) + \eta d(n_0) + \alpha w_{ij}(n_0) \tag{2}$$

3. The VSS with inclusion of the MT algorithm (VSS + MT)

$$\omega_{ij}(n_0 + 1) = \omega_{ij}(n_0) + \eta(n_0)d(n_0) + \alpha w_{ij}(n_0) \tag{3}$$

4. The Levenberg−Marquardt (LM) algorithm

$$\omega_{ij}(n_0 + 1) = \omega_{ij}(n_0) - 2(H + \mu D_H)^{-1}\nabla E(\omega_{ij}(n_0)) \tag{4}$$

where $\eta(n_0)$ is the variable step function; $d(n_0)$ is the gradient of the error variation concerning the weight; η is the stride; α is the momentum factor; H is the Hessian matrix of energy function E at $\omega_{ij}(n_0)$; D_H is the diagonal array with the same diagonal elements as H; and ∇E is the matrix of derivatives of E at $\omega_{ij}(n_0)$.

2.2. GA-BP Neural Network. Conventional BP algorithms are inherently limited by the random generation of initial weights and thresholds, causing issues such as sluggish convergence and a large number of training iterations when gradient changes are minute. Furthermore, these algorithms may converge to a local minimum instead of the global minimum of the objective function. To overcome these limitations, advanced BP algorithms have been proposed that build on the traditional BP model. The GA-BP network structure is depicted in Figure 2, illustrating the main modifications:[31]

The following steps are employed to optimize a BP neural network with a genetic algorithm:

1. Establish a BP neural network model according to specific circumstances and initialize its parameters.
2. Use the genetic algorithm to optimize the constructed BP neural network model, design the fitness function of the genetic algorithm based on the objective function in the BP network, and then optimize the initial weights and thresholds of the BP neural network utilizing the fitness function to obtain optimal initial weights and thresholds. The specific steps include the following. (1) Initialization: Randomly generate an initial population and set the size of the population, number of iterations, etc. (2) Calculation of the fitness value: After obtaining the initial population, calculate the fitness value of each individual. (3) Selection: Screen the individuals in the population, and then transfer superior individuals to the next generation. (4) Crossover: Randomly select two individuals from the population and perform crossover operations to form a new individual. Repeat this step until all target individuals have been crossed. (5) Mutation: Based on the set mutation probability, search for several individuals in the population and perform mutation operations on them. (6) Determine whether the algorithm meets the stop condition. If so, the algorithm ends and the optimal solution to the problem is obtained. Otherwise, return to step (2) and continue iterating.
3. Train the BP neural network model optimized by the genetic algorithm.
4. If the output value of the network meets the condition, the network calculation process ends, and the result is the output.

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Table 1. Evaluation Index System for Steep Coal Seam Mining Methods

serial number	influencing factor	quantitative index		
1	coal seam thickness	average thickness of coal seam (x_0)		
2	coal seam dip	average dip of coal seam (x_1)		
3	coal seam hardness	compressive strength of coal (x_2)		
		compressive strength of gangue (x_3)		
4	coal seam variability	coefficient of variation of coal thickness (x_4)		
5	coal seam admissibility	coal seam recoverability index (x_5)		
6	coal bed gangue	coal bed gangue rate (x_6)		
7	immediate roof	compressive strength of immediate roof (x_7)		
8	false roof	false roof thickness (x_8)		
9	floor	compressive strength of floor (x_9)		
10	mining face length	average length of working face (x_{10})		
11	mining face advancing length	average advancing length of mining face (x_{11})		
12	fault	number of faults (x_{12})		
		fault length index (x_{13})		
		fault drop coefficient (x_{14})		
13	fold	folding strength coefficient (x_{15})		
		folding complexity coefficient (x_{16})		
14	gas	low gas concentration	1	(x_{17})
		high gas concentration	0.6	
		gas outburst anomaly	0.3	
		coal and gas outburst	0	
15	hydrology	arid	1	(x_{18})
		nonaqueous	0.6	
		moderately aqueous	0.3	
		excessively aqueous	0	
16	spontaneous combustibility	absence	1	(x_{19})
		low likelihood	0.6	
		moderate likelihood	0.3	
		high likelihood	0	

3. MINING METHOD EVALUATION MODEL FOR STEEP COAL SEAMS

3.1. Evaluation Index System for Steep Coal Seam Mining Methods. To ensure that the model possessed adequate fitting capacity, constructing an evaluation index system composed of factors related to mining techniques for steep coal seams was imperative before the neural network model. The evaluation index system for steep coal seam mining methods was determined through a combination of various factors. Based on the geological conditions of steep coal seams, this paper considered four factors, including coal seam occurrence conditions, roof–floor conditions, working face conditions, and other conditions. Ultimately, 16 self-criteria were determined for the evaluation of steep coal seam mining methods. These criteria included the coal seam thickness, coal seam dip, coal seam hardness, etc. The evaluation index system is depicted in Figure 3. Because the neural network outputs through input data, qualitative indicators cannot be accurately and effectively input into the neural network. Hence, quantification of the factors affecting the evaluation is crucial in establishing the neural network model. Therefore, it was necessary to quantify the 16 subcriteria. The quantified results are listed in Table 1.

3.2. Structure Design of the Neural Network. The crux of establishing a BP neural network model lies in determining the optimal number of unit nodes, which entails ascertaining the appropriate quantity of nodes in the input, output, and hidden layers. The initial step in identifying the unit nodes involved using 50 sets of workforce data collected from eight Guizhou mines as learning samples, acquired through field surveys and data collection. Subsequently, 30 learning samples were randomly selected as the training set, 10 as the test set, and 10 as the validation set.

Input layer: The input layer of the neural network model for assessing steep coal seam mining methods consisted of the indices employed to evaluate the mining methods. Developing the input layer entailed the identification of these evaluation indices. In keeping with the practical conditions of steep coal seam mining, a BP neural network model for assessing mining methods was created. The input layer of the neural network contained 20 neurons, denoted as $x = (x_0, x_1, ..., x_{19})^T$.

Output layer: To satisfy the demands of appraising steep coal seam mining methods, the said process was designated as the output parameter of the BP neural network, denoted as $y = (y_0, y_1, \text{and } y_2)^T$. Before commencing network training, the network output values were predetermined as follows: "0.9, 0.1, 0.1" for fully mechanized mining, "0.1, 0.9, 0.1" for ordinary mining, and "0.1, 0.1, 0.9" for blast mining. The resulting output denoted fully mechanized mining if y_0 represented the maximum value, ordinary mining if y_1 represented the maximum value, and blast mining if y_2 represented the maximum value. Furthermore, as y_0, y_1, and y_2 approach 0.9, they signify a higher suitability for fully mechanized mining, ordinary mining, and blast mining under the working face.

Hidden layer: The numbers of hidden layers and nodes within the BP neural network play a pivotal role in determining the predictive accuracy of the said neural network. Insufficient layers and nodes hinder the network's capacity to learn, while an excessive number of nodes may lead to overfitting. To ascertain

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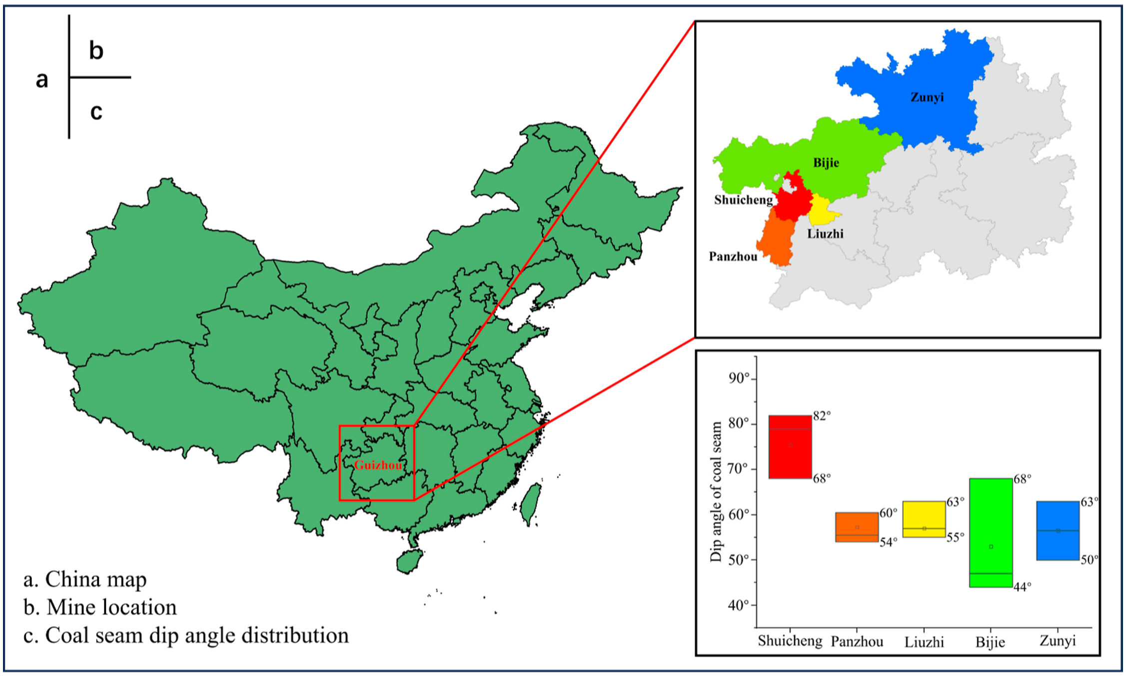

Figure 4. Project background and statistics. (a) Map of China. (b) Mine locations. (c) Coal seam dip angle distribution.

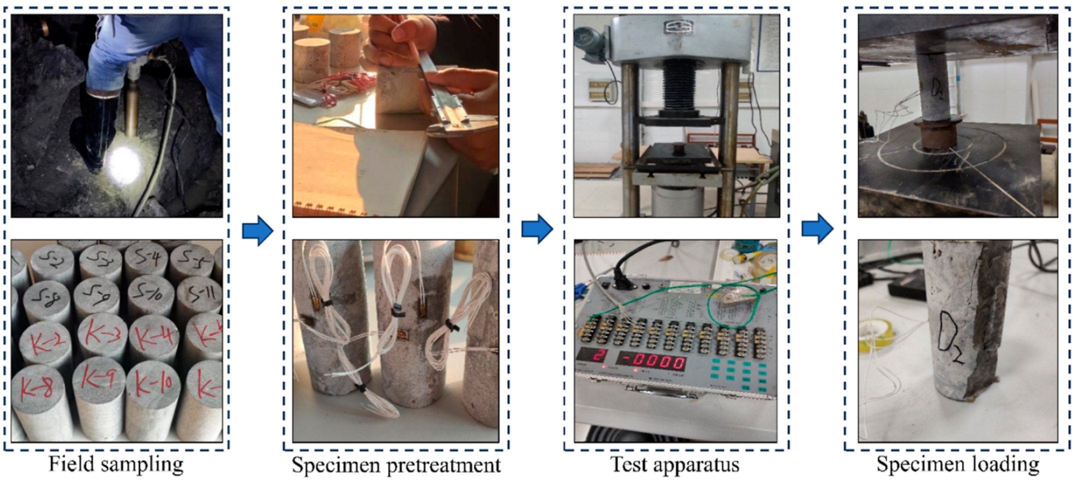

Figure 5. Rock mechanical test procedure.

the optimal number of hidden layer nodes, formula 5 was employed[33]

$$L \leq \sqrt{(M + N)} + A \tag{5}$$

where L is the number of nodes in the hidden layer; N is the number of nodes in the input layer; M is the number of output layer nodes; and A is a constant between 0 and 10.

3.3. Data Acquisition and Analysis. The Guizhou mining region is endowed with abundant steep coal resources with a concentrated distribution of thin-to-medium thick coal seams in areas such as Liuzhi, Zunyi, and Shuicheng. Notable among these are the C14, C15, C16, C17, C18, C19, and C29 coal seams of the Changyin Coal Mine in Shuicheng County; the C5, C3, and C1 coal seams of the Wanshun Coal Mine in Tongzi County; and the #1, #3, #7, #17, #18, and #21 coal seams of the Xingwang Coal Mine in the Liuzhi Special District. According to incomplete statistics, the cumulative reserves of steep coal seams in the aforementioned mines are approximately 62.603, 29.54, and 19.927 million tonnes, respectively.[32]

Driven by demand, this study's research team embarked on a comprehensive exploration of numerous coal mines in Shuicheng, Panzhou, Liuzhi, Bijie, and Zunyi and diligently conducted surveys and compiled data regarding the major mines and mining faces. The project context and dip angle distribution are illustrated in Figure 4.

The surveyed mines are acknowledged to be urgently in need of renovation, requiring an efficient approach to discern an appropriate extraction technique, in accordance with the geological attributes of each mine. Resolution of this issue will expedite progress in the extraction of challenging coal seams, enhance working conditions, and realize secure and efficient mining operations. In turn, such an approach will provide the essential theoretical foundation to improve the mechanization level within China's coal industry, achieving harmonious alignment with the developmental objectives of the coal sector.

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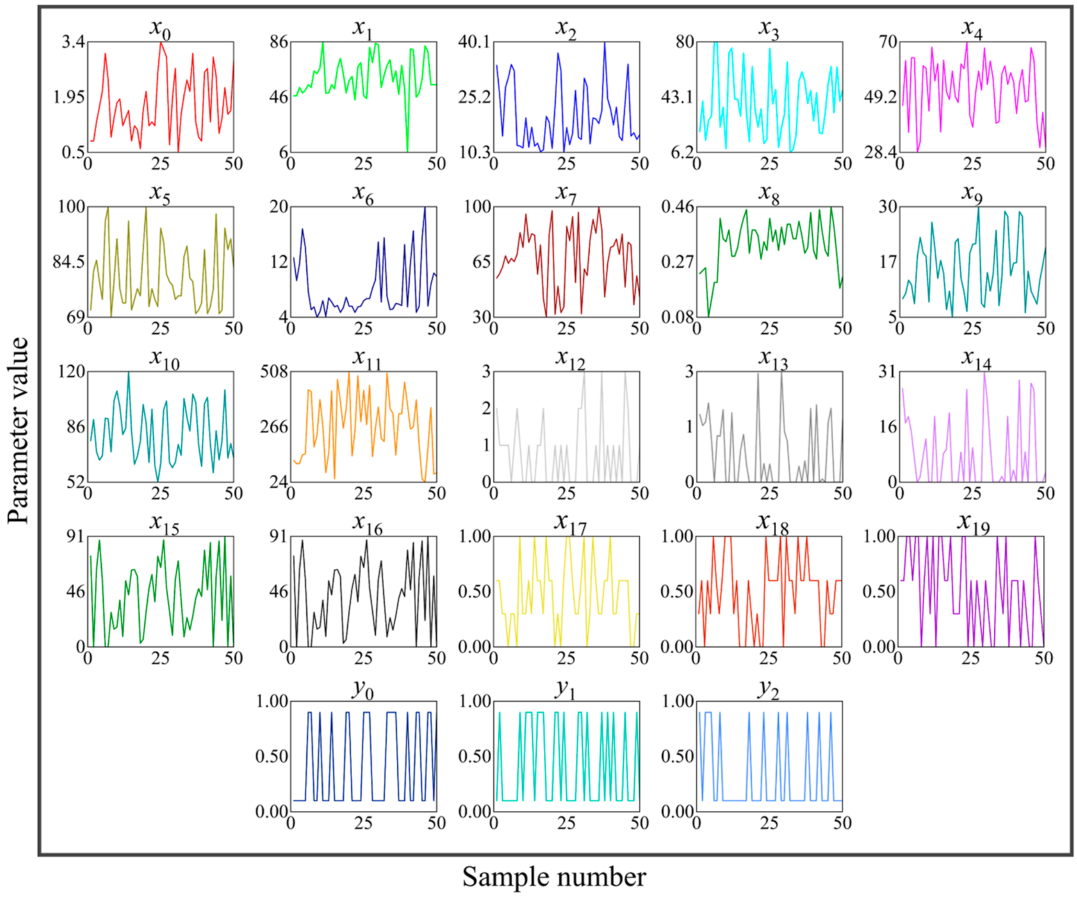

Figure 6. Sample data for training the neural network.

Employing economic, technological, and environmental considerations as our evaluation criteria, we judiciously handpicked 50 workfaces from the steep coal seams evaluated during on-site investigations. These selections were predicated on their distinct aptness for contemporary extraction methodologies in the coal mining domain. Subsequently, we conducted on-site sampling and performed mechanical experiments (depicted in Figure 5) to procure missing data related to coal seam characteristics. The data sets utilized for training the neural network are presented in Figure 6 (https://1drv.ms/x/s!AhFxzUt5Rfw5gnuFMxIm-suIv2LJ?e=CFo7sk).

To circumvent the scenario where insignificant data may get overshadowed by substantial data, rendering the evaluation outcomes subpar, formula 6 is employed to standardize the initial data.[17]

$$Y_k = \frac{X_k - X_{min}}{X_{max} - X_{min}} \quad (6)$$

where Y_k is the data obtained by preprocessing, X_k is the original data, X_{min} is the minimum value in the sample series, and X_{max} is the maximum value in the sample series.

To ascertain the impact of each factor on the prediction outcome and eliminate sources of minor variability in the data in order to enhance the model's sensitivity to true signals, correlation analysis was conducted on 50 sets of sample data. To determine the appropriate method for correlation analysis, it was necessary to ascertain whether the sample data followed a normal distribution. Spearman correlation analysis was conducted when the data followed a normal distribution, whereas Pearson correlation analysis was conducted for non-normal distribution of the data. Thus, histograms of each factor were plotted, as shown in Figure 7, which revealed that the sample data did not conform to a normal distribution overall. Spearman correlation analysis was subsequently employed to determine the impact of each factor on the prediction outcome.

Spearman correlation analysis was conducted on 50 sets of samples by using SPSS software, and the results are depicted in Figure 8. Except for false roof thickness (x_8), hydrology (x_{18}), and spontaneous combustibility (x_{19}), the correlation of the remaining input parameters with the output parameter exceeded 0.2. Among them, the coal seam recoverability index (x_5) was the primary source of variability for fully mechanized and ordinary mining, with correlation coefficient (R) values of 0.78 and −0.46, respectively. Additionally, the compressive strength of coal (x_2) was the primary variability source for blast mining, with an R value of 0.49. Based on this analysis, x_8, x_{18}, and x_{19} were excluded, while the remaining parameters were retained as input variables for the neural network.

3.4 Hyperparameters Tuning. Hyperparameters serve as the tuning knobs that control the model's structure, functionality, and efficiency. For the BP neural network, the hyperparameters included the learning rate, epochs, target error, number of hidden layer units, and activation function, while for GA, they encompassed population size, evolutional times, crossover probability, and mutation probability. The results of multiple experiments revealed that the experimental requirements were met when the number of epochs was set to 1000 and the target error was 1×10^{-5}. Thus, these parameters were not considered in hyperparameter tuning.

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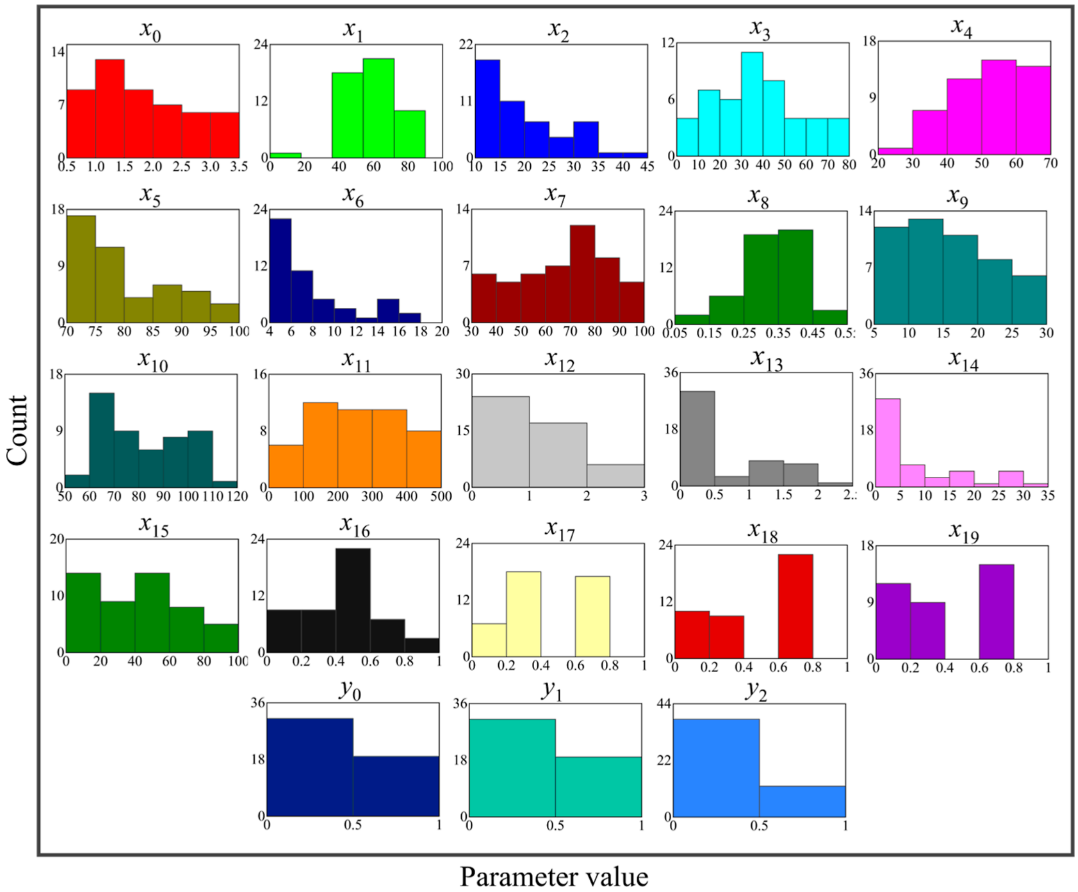

Figure 7. Histogram of the input parameters.

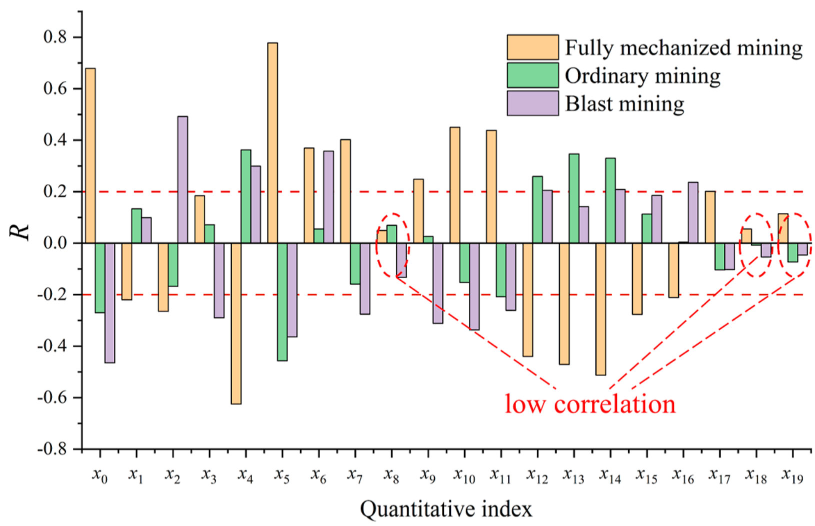

Figure 8. Correlation analysis results of each factor.

Table 2. Factors and Levels

levels	learning rate	number of hidden layer units	activation function	population size	evolutional times	crossover probability	mutation probability
1	0.0001	1	elu	20	50	0.2	0.001
2	0.001	5	tanh	40	100	0.4	0.01
3	0.01	9	relu	60	150	0.6	0.1
4	0.1	13	sigmoid	80	200	0.8	0.2

To determine the optimal conditions for the remaining parameters, the standard BP algorithm was employed as the training model for the GA-BP neural network. An experimental study was conducted by adopting an orthogonal experimental

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Table 3. Test Scheme

scheme number	learning rate	number of hidden layer units	activation function	population size	evolutional times	crossover probability	mutation probability
1	0.0001	9	3	80	200	0.8	0.1
2	0.1	5	4	40	200	0.6	0.001
3	0.1	13	2	60	50	0.4	0.1
4	0.001	1	3	80	50	0.4	0.001
5	0.001	5	3	40	100	0.2	0.2
6	0.001	9	1	20	200	0.6	0.1
7	0.0001	5	1	60	100	0.4	0.2
8	0.001	13	1	60	150	0.8	0.01
9	0.01	5	3	20	50	0.8	0.01
10	0.001	9	4	60	50	0.6	0.2
11	0.0001	1	4	60	200	0.2	0.01
12	0.01	1	2	20	150	0.6	0.2
13	0.01	9	1	40	150	0.4	0.001
14	0.01	1	3	60	100	0.6	0.1
15	0.01	13	4	40	50	0.2	0.1
16	0.1	9	2	20	100	0.2	0.01
17	0.01	13	1	80	200	0.2	0.2
18	0.0001	13	3	40	150	0.6	0.01
19	0.1	1	1	40	100	0.8	0.1
20	0.1	9	3	60	150	0.2	0.001
21	0.1	1	4	80	150	0.8	0.2
22	0.01	5	2	60	200	0.8	0.001
23	0.01	9	4	80	100	0.4	0.01
24	0.1	13	3	20	200	0.4	0.2
25	0.001	5	2	80	150	0.2	0.1
26	0.0001	5	4	20	150	0.4	0.1
27	0.0001	9	2	40	50	0.8	0.2
28	0.001	13	4	20	100	0.8	0.001
29	0.001	1	2	40	200	0.4	0.01
30	0.1	5	1	80	50	0.6	0.01
31	0.0001	1	1	20	50	0.2	0.001
32	0.0001	13	2	80	100	0.6	0.001

Table 4. Network Training Parameters

BP algorithm parameters	parameter value	GA algorithm parameters	parameter value
Iterations	1000	population size	60
target error	1×10^{-5}	evolutional times	50
learning rate	0.001	crossover probability	0.6
activation function	sigmoid	mutation probability	0.2
number of hidden layer units	9		

design, with the experimental factors and levels listed in Table 2 and the experimental design detailed in Table 3, with each scheme repeated 20 times for training. The experimental metric was the average coefficient of determination (R^2) obtained from 20 training iterations for each scheme, as depicted in Figure 9.

The experimental results indicated that there were considerable differences in the R^2 value among the 32 schemes. Among them, scheme 10 exhibited the highest R^2 value of 0.499, the lowest R^2 value of 0.183, and an average R^2 value of 0.452, and it was thus selected as the optimal scheme. The hyperparameters used in subsequent experiments are given in Table 4.

Ultimately, the GA-BP neural network structure was established as “17-9-3”.

4. RESULTS

The comparative study of the model was primarily divided into the following aspects: (1) a comparative analysis of BP neural network algorithms trained with the traditional BP, VSS, MT, VSS + MT, and LM algorithms to determine the most suitable BP neural network algorithm for the problem at hand and (2) a comparison of models trained by the GA-BP and BP neural networks, analyzing whether the GA-BP neural network demonstrated significantly improved accuracy compared to the BP neural network.

4.1. Comparative Analysis of BP Algorithms. Employing the parameter values listed in the BP section of Table 4, the traditional BP, VSS, MT, VSS + MT, and LM algorithms were each trained 20 times. The training results are presented in Table 5. The VSS + MT and LM algorithms had successful convergence with 20 iterations, while the other algorithms experienced convergence failures. Notably, the traditional BP and MT algorithms only had 0 and 2 successful convergence iterations, respectively. The VSS + MT algorithm had average, maximum, and minimum iteration counts of 305, 455, and 53, respectively, while the LM algorithm had average, maximum, and minimum iteration counts of 314, 538, and 67, respectively.

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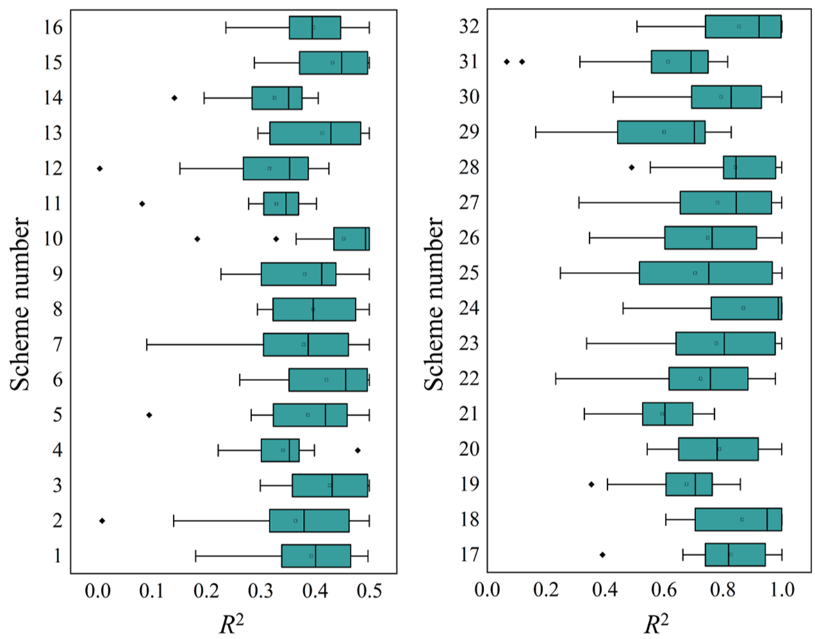

Figure 9. Diagram of superparameter optimization results for each scheme.

Table 5. Results of BP Neural Network Training with Different Algorithms

BP algorithm	number of successful convergence	average number of iterations	maximum number of iterations	minimum number of iterations
Standard	0	>1000	>1000	>1000
VSS	13	891	>1000	224
MT	2	>1000	>1000	950
VSS + MT	20	305	455	53
LM	20	314	538	67

The iteration counts for both algorithms were substantially lower than those of the other algorithms. The aforementioned analysis indicated that the VSS + MT and LM algorithms had convergence success rates and efficiencies higher than those of the other algorithms. The iteration counts of each BP algorithm are illustrated in Figure 10.

To determine the optimal algorithm for the present problem, further analysis of the strengths and weaknesses of each algorithm in the evaluation model was imperative. The error variance attained by the VSS, VSS + MT, and LM algorithms was compared, as depicted in Figure 11. Analysis of the training results indicated that the BP neural networks trained with the VSS, VSS + MT, and LM algorithms obtained mean squared error (MSE) values of 0.2185, 0.1490, and 0.2685, respectively, with minimum squared errors of 0.08, 0.04, and 0.14, respectively. Notably, the BP neural network trained with the VSS + MT algorithm had the lowest squared error.

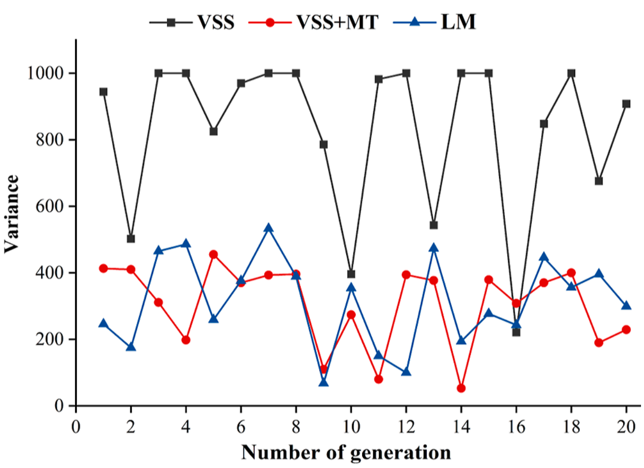

Figure 10. Comparison of BP algorithm iteration number results.

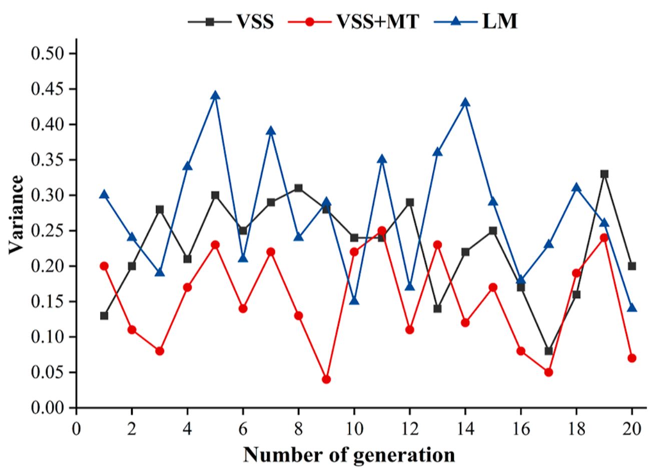

Figure 11. Variance test of BP network training with different algorithms.

In summary, when juxtaposed with the other four algorithms, the BP neural network trained with the VSS + MT algorithm boasted the benefits of a high convergence success rate, high convergence efficiency, and minimal error variance. Therefore, the VSS + MT algorithm was employed in training the coal mining method assessment network model for steep coal seams.

4.2. Training Model Optimization. To guarantee the reliability of the comparison results between the BP and GA-BP models, the following limitations were imposed: (1) both models utilized the data in the training set as test samples; (2)

both models employed the VSS + MT algorithm as the neural network algorithm; (3) roulette wheel selection was used as an evolutionary algorithm in genetic algorithms; and (4) both models used the parameters outlined in Table 4 as the training parameters of the network. Based on the abovementioned conditions, the average fitness and optimal fitness of the GA-BP model were calculated to be 4.04184×10^{-6} and 1.295×10^{-7} (depicted in Figure 12), and the best initial weights and thresholds for the GA-BP model were obtained. These statistics were employed in the ensuing comparison of the BP and GA-BP models.

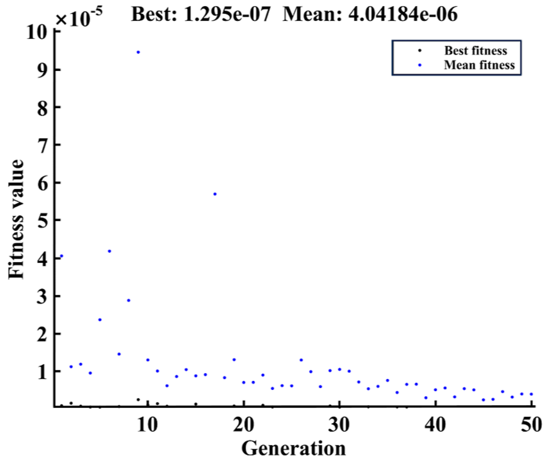

Figure 12. Optimization process of the genetic algorithm.

The BP and GA-BP models were assessed independently. The BP model obtained $R^2 = 0.79$ and MSE = 0.06, whereas the GA-BP model obtained $R^2 = 0.85$ and MSE = 0.04, as depicted in Figure 13. A higher R value and a lower MSE value indicated greater algorithmic accuracy. Thus, the GA-BP model outperformed the BP model.

4.3. Verification. Subsequently, the model underwent validation to ensure that it satisfied the anticipated assessment standards for steep coal seam mining methods. Ten data sets from the prediction set were utilized to simulate the prediction outcomes of the BP and GA-BP models. The prediction outcomes of the BP and GA-BP models are presented in Figure 14, and the prediction errors of evaluation values I–III are displayed in Table 6.

As shown in Table 7, the GA-BP model exhibited higher average errors for evaluation values I, II, and III in comparison to the BP model. In a sample of 10 instances, the BP neural network accurately predicted the mining method in seven cases, achieving a success rate of 70%. By contrast, the GA-BP neural network achieved nine successful predictions, with a success rate of 90%. These results underscore that optimizing the BP neural network's weights and thresholds through a genetic algorithm can meaningfully enhance the network's predictive accuracy. Accordingly, the prediction outcomes of the GA-BP model in identifying the appropriate mining method for steep coal seams were more precise than those of the BP neural network model, validating the superiority of the GA-BP model.

5. CASE ANALYSIS

The coal seam of the evaluated working face in the Zhong-Yu coal mine has a dip angle ranging from 52 to 58°, with an average of 55°. The coal seam is of bright black powder coal type, containing 0–2 dirt bands, and has a simple structure, making it a stable coal seam that can be fully exploited in the entire region. The top plate is composed of mudstone, while the base plate is composed of clayey mudstone. The average coal thickness of the working face is 2.5 m, and the coal seam has a simple structure, with stable occurrence, a strike length of 405 m, and a dip length of 120 m. The upper part of the face is an old goaf, which can infiltrate locally through faults and roof fractures. Water seepage and dripping in the goaf may occur during the mining process. To further analyze the superiority of the trained model in the context of this case, an evaluation and prediction of the appropriate mining process were performed based on the parameters of this working face. The relevant parameters are listed in Table 8.

After inputting the normalized data obtained from Table 8 into the well-established GA-BP neural network model, the working face was assigned an evaluation index of "0.847, 0.09, 0.111", suggesting that a fully mechanized mining process should be implemented, which aligned with the prevailing on-site conditions.

6. CONCLUSIONS

When evaluating coal mining technology, traditional expert-based selection methods often suffer from subjectivity and inefficiency in the decision-making process. However, employing the GA-BP neural network for selecting coal mining methods has partially addressed these issues. This approach provides

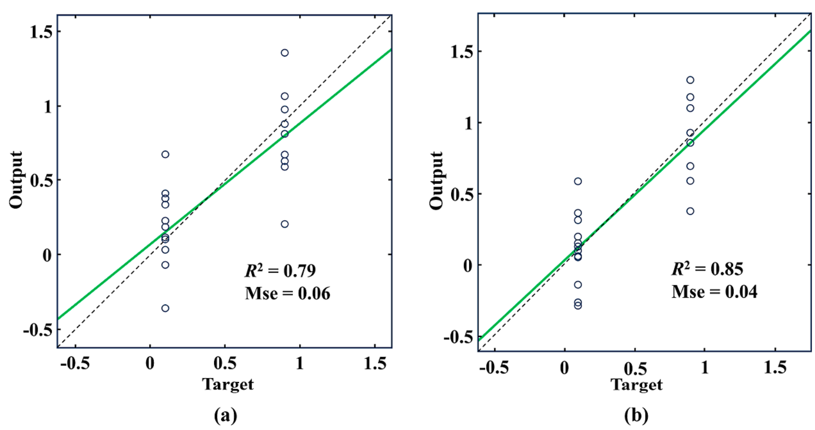

Figure 13. Comparison of the GA-BP and BP models at the testing stage: (a) BP and (b) GA-BP.

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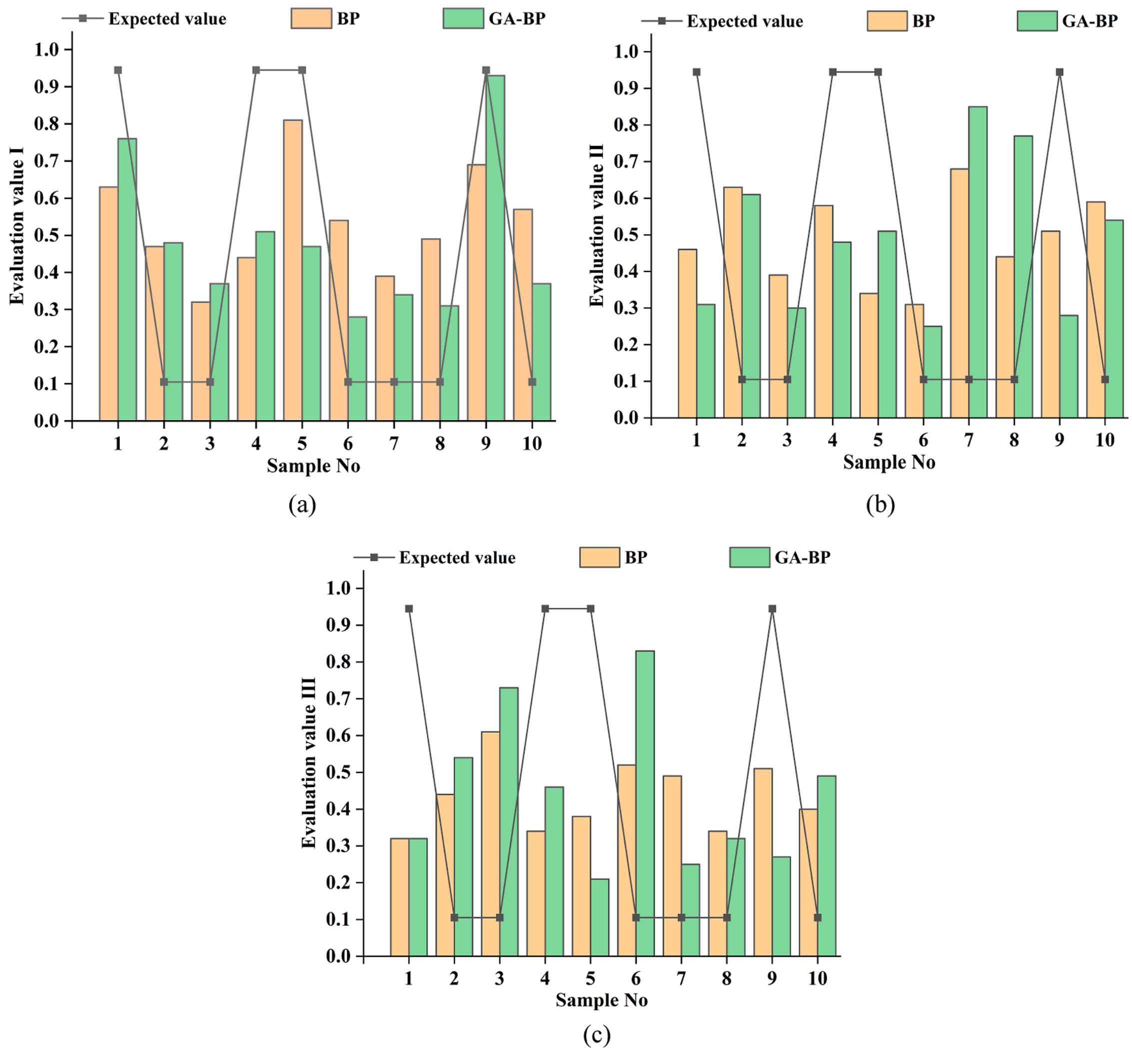

Figure 14. Comparison of GA-BP and BP model prediction results: (a) evaluation value I, (b) evaluation value II, and (c) evaluation value III.

Table 6. Prediction Errors of the BP and GA-BP Models

	evaluation value I				evaluation value II				evaluation value III			
	BP		GA-BP		BP		GA-BP		BP		GA-BP	
sample no	E	$\overline{E}$	E	$\overline{E}$	E	$\overline{E}$	E	$\overline{E}$	E	$\overline{E}$	E	$\overline{E}$
1	0.27	0.321	0.14	0.254	0.36	0.325	0.21	0.236	0.22	0.309	0.22	0.230
2	0.37		0.38		0.27		0.29		0.34		0.44	
3	0.22		0.27		0.29		0.20		0.29		0.17	
4	0.46		0.39		0.48		0.38		0.24		0.36	
5	0.09		0.43		0.24		0.41		0.28		0.11	
6	0.44		0.18		0.21		0.15		0.38		0.07	
7	0.29		0.24		0.22		0.05		0.39		0.15	
8	0.39		0.21		0.46		0.13		0.24		0.22	
9	0.21		0.03		0.41		0.18		0.41		0.17	
10	0.47		0.27		0.31		0.36		0.30		0.39	

objective and efficient selection solutions for the renovation of coal mines in Guizhou while also offering valuable experience for similar problems in other industries.

Herein, a system for evaluating mining methods for steep coal seams was established. This system takes into account four critical factors, including coal seam conditions, roof and floor conditions, working face conditions, and other conditions. In total, 20 factors were identified. Spearman correlation analysis revealed that other than false roof thickness, hydrology, and spontaneous combustibility, the remaining factors were the primary sources of variability.

Taking the hyperparameters of the BP neural network and genetic algorithm as experimental factors and utilizing the coefficient of determination (R^2) as the experimental metric, an orthogonal experimental design was employed to determine the optimal hyperparameter values for the GA-BP neural network.

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Table 7. Evaluation Results of BP and GA-BP Model Validation

	output value		evaluation result		
no	BP	GA-BP	BP	GA-BP	mining method
1	(0.63,0.46,0.32)	(0.76,0.31,0.32)	fully mechanized mining	fully mechanized mining	fully mechanized mining
2	(0.47,0.93,0.44)	(0.48,0.61,0.54)	ordinary mining	ordinary mining	ordinary mining
3	(0.32,0.39,0.81)	(0.37,0.30,0.73)	blast mining	blast mining	blast mining
4	(0.44,0.58,0.34)	(0.51,0.48,0.46)	ordinary mining	fully mechanized mining	fully mechanized mining
5	(0.81,0.34,0.38)	(0.47,0.51,0.21)	fully mechanized mining	ordinary mining	fully mechanized mining
6	(0.54,0.31,0.52)	(0.28,0.25,0.83)	fully mechanized mining	blast mining	blast mining
7	(0.39,0.68,0.49)	(0.34,0.85,0.25)	ordinary mining	ordinary mining	ordinary mining
8	(0.49,0.44,0.34)	(0.31,0.77,0.32)	fully mechanized mining	ordinary mining	ordinary mining
9	(0.69,0.51,0.51)	(0.93,0.28,0.27)	fully mechanized mining	fully mechanized mining	fully mechanized mining
10	(0.57,0.59,0.40)	(0.37,0.54,0.49)	ordinary mining	ordinary mining	ordinary mining

Table 8. Parameters of a Working Face in Zhong-Yu Coal Mine

index	name	raw data	normalized data
1	coal seam thickness	2.5 m	0.571
2	coal seam dip	55°	1
3	compression strength of coal seam	32 MPa	0.733
4	compression strength of gangue	67 MPa	0.827
5	coal seam variability	15%	0.071
6	coal seam admissibility	100%	1
7	coal bed gangue rate	9.3%	0.331
8	immediate roof	69 MPa	0.557
9	floor	23 MPa	0.72
10	mining face length	80 m	0.429
11	mining faces advancing length	450 m	0.891
12	fault	1 band/km^2	0.333
13	fault length index	0 km/km^2	0
14	drop coefficient of fault	0%	0
15	fold	0%	0
16	fold complexity coefficient	0 rad/km^2	0
17	gas	0	0

The optimized hyperparameter values were determined as follows: iterations, 1000; target error, 1×10^{-5}; learning rate, 0.001; activation function, sigmoid; hidden layer units, 9; population size, 60; evolutional times, 50; crossover probability, 0.6; and mutation probability, 0.2. Consequently, the GA-BP neural network structure was confirmed to be "17-9-3".

During the training phase, under equal conditions, the successful iteration count, average iteration count, mean variance, and minimum variance of the BP neural network trained with the VSS + MT algorithm were 20, 305, 0.1490, and 0.04, respectively. The R^2 and MSE values obtained from training the GA-BP model were 0.85 and 0.04, respectively. The VSS + MT algorithm outperformed other algorithms, and the GA-BP model exhibited a superior performance compared to the BP model. In the prediction phase, the GA-BP model achieved a success rate 20% higher than that of the BP model, which aligned with our expectations.

Subsequently, the model was applied to the evaluated working face of the Zhong-Yu coal mine, and the evaluation index for the working face conditions was determined to be "0.847, 0.09, 0.111". The obtained evaluation result was consistent with the current production status of the mine, attesting to the dependability of the GA-BP model in the field.

The study findings can serve as a point of reference for analogous inquiries. Initially, we incorporated all coal seams with varying dip angles as learning samples for the GA-BP neural network, yet the output accuracy consistently fell short of our ideal expectations. Consequently, we developed an exploitation feasibility evaluation model solely for steep coal seams. To address this limitation, we intend to establish an exploitation feasibility evaluation model suitable for coal seams with steep dip angles, thereby enhancing the universality of this approach.

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Notes

The authors declare no competing financial interest.

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NOMENCLATURE

BP	backpropagation neural network
ANN	artificial neural network
GA	genetic algorithm
VSS	variable step size algorithm
MT	algorithm by appending momentum term
VSS + MT	variable step size algorithm with the inclusion of momentum term
LM	Levenberg−Marquardt algorithm
ω	weight
η	variable step function

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d	gradient of the error variation concerning the weight
n	stride
α	momentum factor
H	Hessian matrix of the energy function E at ω_{ij} (n_0)
D_H	diagonal array with the same diagonal elements as H
∇E	matrix of derivatives of E at $\omega_{ij}(n_0)$
Y_k	normalization data
X_k	original data
X_{min}	minimum value
X_{max}	maximum value
L	number of nodes in the hidden layer
M	number of nodes in the input layer
N	number of nodes in the output layer
A	a constant between 0 and 10
R	correlation coefficient
R^2	coefficient of determination
MSE	mean squared error

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