Research Article

Multiscale Intelligent Inversion of Water-Conducting Fractured Zone in Coal Mine Based on Elastic Modulus Calibration Rate Response and Its Application: A Case Study of Ningdong Mining Area

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Water-conducting fractured zone is the direct inducement of water inrush, water losing, and environmental deterioration in coal mines. How to predict the height of water-conducting fractured zone economically and accurately has always been the research difficulty of water-preserved mining. The paper selects the Meihuajing coal mine in Ningdong mining area as the engineering background. Firstly, transform the distribution law of the water-conducting fractured zone into a deterioration mechanism of coal-rock strength under the action of water-rock. Through laboratory tests, the water-rock coupling degradation law of rock mass under uniaxial action is revealed, and an intelligent statistical model of damage rate response under different water content is proposed. Secondly, based on the cross-scale elastic modulus calibration principle and the rate response intelligent statistical model proposed above, the borehole elastic modulus instrument is used to quantitatively characterize the strength characteristics of elastic modulus rate response law and field lithological parameters. Finally, based on the 18 samples of the water-conducting fractured zone, a height prediction model of a water-conducting fractured zone based on the measured value of elastic modulus is proposed by using the method of PSO-SVR. Taking R² and RMSE as evaluation indexes, the error comparison between PSO-SVR and the empirical formula is carried out. Research indicates that, compared with the empirical formula, R² of the PSO-SVR model increased by 18.3% and RMSE decreased by 92.7%. The predicted value of the PSO-SVR is consistent with the measured value, which significantly improves the prediction accuracy of the height of the water-conducting fractured zone. It provides a theoretical basis and technical support for the coordinated development of safe and efficient development of coal and ecological protection in Ningdong mining area.

1. Introduction

In recent years, with the gradual increase of mining depth and mining intensity in western mining areas of China, the problems of large-scale rock fracture caused by the development and expansion of mining fractures are becoming more and more serious [1, 2]. The traditional mining concept and technology cannot fully adapt to the current strong mining conditions with long working face, large mining height, and fast advancing. There is an urgent need to update relevant theories through artificial intelligence, big data, and other methods. Ningdong mining area is located in arid and semiarid areas with fragile ecological environments. Environmental problems such as water resource damage and surface subsidence caused by strong mining are more prominent [3, 4]. The height of water-conducting fractured zone is a key parameter for water-preserved mining [5]. Therefore, economically and accurately predicting the height of the water-conducting fractured zone is an important measure to realize green
mining in arid and semiarid mining areas in Western China.

Given the above problems, the height prediction methods of water-conducting fractured zone mainly include empirical formula, theoretical calculation, similar simulation, and numerical simulation. Fan et al. [6] believe that the empirical formula proposed in the 20th century is no longer applicable to the current mining conditions. The prediction model is an important research direction in water-preserved mining. Fan et al. [7] believe that field test is the best method to study the water-conducting fractured zone, but it is time-consuming, laborious, and costly. The model parameters of numerical simulation are closely related. Guo et al. [8] believe that the theoretical model of fracture zone established at present is too idealized and deviates greatly from the geological characteristics of the site. Zhang et al. [4, 9] conducted a study on the characteristics of the site. Zhang et al. [4, 9] conducted a study on the "domino effect" of overlying rock deformation under the mining influence through physical simulation experiments. A surface damage reduction system based on short-wall block backfilling (SBBM) method is further proposed, which effectively controls the further development of water-conducting fractured zones. Cao et al. [10] based on the self-developed simulation platform revealed the evolution characteristics of the water-conducting fractured zone in the process of coal-water coordinated mining. However, the platform is difficult to simulate some complex geological conditions. Therefore, the accurate and economic calculation of the height of fractured zone through neural networks, machine learning, and other methods is the direction that we should focus on. Wu et al. [11], based on a large amount of field data such as core, microseismic, and production in underground engineering, proposed an effective method that integrates stochastic CFN modeling, reservoir simulation, and auxiliary history matching to characterize complex fracture networks (CFN) and reduce uncertainty method. Some experts [12, 13] used intelligent algorithms to predict the height of the fractured zone. However, BP has some problems, such as slow speed and easy to fall into a local minimum, which has a certain impact on the accuracy and generalization ability of the model. Elman has poor reliability. To achieve the target accuracy, the number of hidden layer neurons is relatively more than others. SVR is a machine learning method. It has the advantages of high precision, fast convergence, and strong generalization ability and has been widely used in engineering [14–16]. The parameters of SVR are important factors affecting its prediction performance. So far, the parameter selection problem can only be optimized by other algorithms [17]. PSO is similar to the GA algorithm proposed by Kennedy. However, it does not need the tedious "crossover" and "mutation" operations of GA, but searches by following the currently searched optimal particles [18]. At present, it has been widely used in function optimization and neural network training. Therefore, using PSO to optimize the parameters in the SVR model will improve the prediction accuracy.

In addition, because the field data at the macro scale do not have advantages inaccuracy, it is impossible to directly promote the refined theoretical research. Therefore, it is still necessary to study the deterioration law of rock by water at the laboratory scale. Many scholars have made a lot of valuable results. Tan et al. [19, 20] based (DIC) and (SHPB) test system conducted an in-depth analysis of the dynamic response and fracture evolution characteristics of the rock mass with holes and revealed the relationship between the crack evolution and failure mode, the number of cavities, and its layout. Chen et al. [21] revealed the softening mechanism of slate after soaking by measuring the changes of water absorption, wetting angle, and the microstructure and porosity of mineral particles under different soaking times. Shao et al. [22] produced different ASPM samples by varying the content of FA (0-30 wt%) and the curing times (3, 7, 14, and 28 days). The mechanical strength test, hydration kinetics test, and microscopic test of aeolian sand paste-like materials (ASPM) were studied. Sun et al. [23] focused on the nonlinear evolution of the transition from pipe flow (PF) to FF during the process of carbonate rock rupture, with a view to determining the mechanism by which the interactions between geological structures and karst PF cause disasters. Yang et al. [24] mainly adopted rock mechanics experiments to accomplish the research on creep behavior and crack evolution of stratified structural sandstone. Zhao et al. [25] accurately predicted the deformation and permeability evolution characteristics of rock samples with rough fractures under unloading conditions by introducing permeability model.

Taking Meihuaing coal mine as the main object, the distribution law of water-conducting fractured zone is transformed into the strength deterioration mechanism of coal-rock mass under the action of water-rock through scale transformation. Combined with laboratory tests, an intelligent statistical model of damage rate response of coal-rock under different water content is proposed. Based on the cross-scale elastic modulus calibration principle, with the help of the statistical model, the strength characteristics of the parameters related to the field lithology are quantitatively described by the borehole elastic modulus instrument. Finally, based on the 18 samples of the water-conducting fractured zone and the PSO-SVR, a height prediction model based on the measured value of elastic modulus is proposed. It provides an economic and accurate prediction model of the water-conducting fractured zone for Ningdong mining area.

2. Test Scheme

2.1. Rock Sample Description and Preparation. The coal and rock samples used in this paper are taken from the mining face of Meihuaing coal mine. According to sampling requirements, the coal and roof shall be sampled in the height direction perpendicular to the joint surface of the coal-rock layer behind the support of the working face. In addition, the specimen shall be processed into a cylinder (50 mm x 100 mm) by following the experimental standards of the International Society for Rock Mechanics.

It is an effective method to observe the microcracks in coal by a scanning electron microscope. The specific diagram of coal and rock samples is shown in Figure 1. To avoid the interference of other factors, the samples are
naturally air-dried for 24 hours and are defined as the natural state. It is approximately considered that the moisture content is the same under the same state. Separately, the samples smaller than and larger than the natural state are obtained by drying and soaking.

Due to space limitation, only the microstructure characteristics of coal samples in their natural state are expounded. The results show that under SEM with different magnification, natural coal samples have a small number of microcracks and the scanning plane is relatively flat. The microstructure is distributed on the surface in the form of micropores and microcracks. The microcracks are irregular strips. When the magnification increases, it can be seen that the number of micropores and microfractures increases, most of them are circular pores, and there are dense areas of massive pores. Fractures are distributed in strips and irregular shapes.

2.2. Test Equipment and Methods. The test equipment is an electrohydraulic servo pressure testing machine, and its axial load and displacement are measured by the supporting signal acquisition system. SAEU2S AE system is selected for monitoring in the experiment. The main amplifier is set to 40 dB, the threshold value is 45 dB, the resonant frequency of the main probe is 20-400 kHz, and the sampling frequency is 1 MHz. Two channels are used to collect data. After applying the coupling agent, the acoustic emission probe is placed relative to the center in the length direction of the test specimen (Figure 2). Each channel corresponds to an independent preamplifier and sensor. During the test, the operation of uniaxial loading and acoustic emission monitoring is started at the same time.

3. Test Results and Analysis

3.1. Analysis of Stress-Strain Characteristics of Coal-Rock in Uniaxial Compression under Different Water Content. In this paper, uniaxial compression tests of coal and rock under three water contents are carried out using rock mechanics testing machine, and the stress-strain curves under different water content are obtained (Figure 3). The test loading mode is the stress control mode. The postpeak curve is distorted and discrete, which is not of research significance. Therefore, this paper mainly discusses the prepeak curve.

Comparing the test results, it can be seen that the prepeak stress-strain curves of coal and rock under three different hydraulic couplings have good similarities. All coal and rock loading processes go through four stages: compaction, elastic (linear), yielding, and failure. With the increase of water content, the compression stage interval of the stress-strain curve of coal increases, the interval of the elastic stage decreases, the yield stage becomes more significant, and the stress-strain curve before the peak of the uniaxial compression test of coal has an overall left-shift compression trend. The reason is that the water molecules in the fractures weaken the cohesive force between the fracture particles so that the coal and rock samples are softened, which further reduces the peak strength and elastic modulus of the coal and rock samples. The macroscopic performance is that the overall mechanical properties are reduced, but due to the fact that the particularity of the hard coal and rock has always maintained the properties of brittle failure, so the peak strain also shows a negative correlation.

3.2. Analysis of Coal and Rock Mechanical Properties in Different Water Content. Extract the corresponding peak strength, peak strain, and elastic modulus, and calculate the softening coefficient in each state. The results are shown in Table 1.

The results show that the mechanical and deformation characteristics of coal and rock have the same trend with the change of water content. With the increase of water content, the peak strength of samples decreases, the peak strain
decreases, and the elastic modulus decreases. For example, the moisture content of coal samples increased from 0 to 5.51%, the peak strength decreased from 32.04 MPa to 21.02 MPa, the peak strain decreased from 0.03500 to 0.02836, and the elastic modulus decreased from 1.40 GPa to 1.10 GPa. The water content of the rock sample increased from 0 to 3.83%, the peak strength decreased from 44.56 MPa to 22.07 MPa, the peak strain decreased from 0.02564 to 0.02120, and the elastic modulus decreased from 3.56 GPa to 1.79 GPa.

Comparing the test results, it can be seen that the mechanical properties of coal and rock samples in different water-bearing states are different, which are embodied in the three mechanical property parameters of peak strength, peak strain, and elastic modulus in Table 1. Referring to the research conclusions of relevant scholars, the peak strength and water content of coal and rock mass show a linear relationship, while the elastic modulus and water content show an exponential function. To more vividly describe the weakening effect of the water content state, the functional relationship between the above mechanical parameters and the water content is fitted. It can be seen from the fitting results (Figure 4) that the peak strength, elastic modulus, and water content function of coal and rock under different states have a good fitting degree, while the peak strain of coal and rock under different states has a positive correlation with water content, which is different from the research results of other scholars. The reason may be that the brittleness has not changed due to its hard property.

### 3.3. Analysis of Coal and Rock Deterioration Effect and Sensitivity under Different Water-Bearing States

To further analyze the deterioration effect of different mechanical parameters and the sensitivity of different mechanical parameters under the same water-rock action state, the corresponding peak strength, peak strain, and elastic modulus in the test data are normalized to calculate the softening coefficient under different states. To establish the functional expression of the deterioration coefficient between water content and mechanical parameters, nonlinear fitting was carried out. It is found that the mechanical parameters and moisture content agree well with the following functions:

\[ Y = m - n \ln X, \]  

(1)
in which $Y$ is the deterioration coefficient of each key mechanical parameter, $m$ and $n$ are the fitting constants, and $X$ is the different water content.

According to the comparison results (Figure 5), the deterioration coefficient of rock samples under water-rock action is greater than that of coal samples. The decreasing trend of each parameter with different water-rock interactions is similar, and the sensitivity influence intensity of each parameter is peak strength > elastic modulus > peak strain.

3.4. Analysis of Coal and Rock Failure Modes under Different Water Content. The failure mode of natural coal samples is shown in Figure 6. The sample is mainly a shear failure, which is a large and obvious main failure shear surface.

\[
y = -5.9693x + 44.026 \\
R^2 = 0.9882
\]

\[
y = -2.0599x + 31.339 \\
R^2 = 0.9347
\]

\[
y = -0.006x + 0.0191 \\
R^2 = 0.8311
\]

\[
y = -0.0002x + 0.0179 \\
R^2 = 0.9055
\]

\[
y = 3.6004e^{-0.177x} \\
R^2 = 0.994
\]

\[
y = 1.3739e^{-0.045} \\
R^2 = 0.9058
\]
penetrating through the sample. The local area presents tensile failure, and small tensile cracks penetrate through the main failure surface. During the loading process, especially when the sample is damaged, the surface has a severe ejection phenomenon and a strong sound. The failure mode of the saturated sample is shown in Figure 7. The main failure mode is tensile failure, which shows that multiple tensile cracks destroy samples together. The strength of natural and saturated samples is quite different, and the failure modes are completely different. During the loading process, the failure of the saturated sample was relatively mild, and there was no ejection and severe noise. The surface cracks were more developed and broken. Under the load of the natural sample, the microcracks in the specimen continuously initiate and expand, forming many small cracks. Under the ultimate load, the series of small tensile cracks assemble into a shear fracture zone after penetrating, in which shear failure suddenly occurs.

3.5. Analysis of Coal and Rock Failure Modes under Different Water Content. Acoustic emission reflects the activity of internal fracture of the loaded rock, and its parameters are closely related to the evolution process of rock damage. To compare the changing relationship of AE parameters, the change law of characteristic parameters such as ring count and energy is obtained by postprocessing the full waveform signal. The AE number is normalized by the cumulative AE number of the whole rock failure process. As shown in Figure 8, the normalized ratio is

\[ n = \frac{N}{N_a}. \]  

The test results show that both the ringing count and energy can better characterize the damage evolution process of the loaded rock, and the energy parameter characterization effect is better, which indirectly indicates that the acoustic emission energy released by rock fracture reveals the essential characteristics of rock destruction.

4. Intelligent Statistical Model of Coal and Rock Damage Rate Response

4.1. Determination of Damage Variables. Based on the randomness of defect distribution in rock, many scholars found that rock microunit strength obeys power function, normal distribution, or Weibull distribution. Combined with the analysis of the uniaxial test, by introducing parameters to describe the law of rock microunit strength distribution, the rock damage evolution equation and damage softening constitutive model are established. Research shows that statistical damage mechanics is one of the effective methods to describe rock failure.

According to the strain equivalent hypothesis proposed by Lemaitre [26], the effective stress is equal to the deformation of the damaged material. That is to say, the strained relationship of the damaged material can be expressed in the form of nondestructive. Only nominal stress \( [\sigma] \) needs to be replaced by effective stress \( [\sigma^*] \). The damage constitutive equation of coal is

\[
[\sigma] = [\sigma^*](I - [D]) = [E][\varepsilon](I - [D]),
\]

in which \( [\sigma^*] \) is the effective stress matrix of rock, \( [\sigma] \) is the nominal stress matrix of the rock, \( I \) is the standard matrix, \( D \) is the damage variable of rock, \( [E] \) is the elastic matrix of rock material, and \( [\varepsilon] \) is the strain matrix of rock.

Assuming that the damage of the coal body is isotropic, the one-dimensional damage constitutive relationship of the coal body can be expressed as

\[
\sigma = \sigma^*(1 - D) = E\varepsilon(1 - D),
\]

in which \( D \) is the damage variable.

The distribution form of power function is simple, which can simplify the calculation and better reflect the damage of coal. Zuo et al. [27] carried out the research on the micro failure of rock-like materials, determined the failure parameters under specific triaxial compression, and further clarified the physical significance of \( m \) in the Hoek Brown criterion. Based on this, this paper introduces the power function to quantitatively describe the rock microelement strength. It is assumed that microelement strength follows the power function distribution, and its probability density function is

\[
P(F) = \frac{m}{F_0^m} \left( \frac{F}{F_0} \right)^{m-1},
\]

in which \( P(F) \) is the rock microelement strength distribution function, \( F \) is the random distribution variable of microelement strength, and \( m \) and \( F_0 \) are distribution parameter,
which reflect the response characteristics of coal body to the external load.

Due to the randomness of microelement failure, when loading to a certain stress level and reaching the microelement strength $F$, the number of microelements that have been damaged is

$$n = \int_0^F NP(x)dx = N \left( \frac{F}{F_0} \right)^m,$$

in which $n$ is the number of microelements that have failed at a certain stress level and $N$ is the total number of microelements.

According to continuum damage mechanics [28], the damage variable is defined as the ratio of the number of damaged microelements to the total number of microelements at a certain stress level, and its expression is

$$D = \frac{n}{N} = \left( \frac{F}{F_0} \right)^m.$$  

in which $F = f(\sigma^*) = a_0 I_1 + J_2^{1/2}$,

$$a_0 = \frac{\sin \phi}{\sqrt{9 + 3 \sin^2 \phi}},$$

$$I_1 = \sigma_x^* J_2 = \frac{1}{3} (\sigma_1^*)^2,$$

in which $\phi$ is the internal friction angle, $I_1$ is the first invariant of stress tensor, $J_2$ is the second invariant of stress devi- ation, $\sigma_1$ is the nominal stress, and $\sigma_1^*$ is the effective stress corresponding to nominal stress.

According to generalized Hook's law,

$$\varepsilon = \frac{\sigma_1^*}{E},$$

$$\sigma_1^* = \frac{\sigma_1}{1 - D},$$

in which $E$ is the elastic modulus of coal and rock sample.

4.2. Determination of Rock Microelement Strength. It is assumed that the failure criterion of rock material is

$$f(\sigma^*) - k_0 = 0,$$

in which $k_0$ is a constant related to the internal friction angle and cohesion of rock materials.

The Drucker-Prager failure criterion is commonly used in all kinds of rock materials, and the parameter form is simple. Therefore, this criterion is used to represent the strength of microelements of rock materials in this paper.

According to continuum damage mechanics [28], the damage variable is defined as the ratio of the number of damaged microelements to the total number of microelements at a certain stress level, and its expression is

$$D = \frac{n}{N} = \left( \frac{F}{F_0} \right)^m.$$  

in which $F = f(\sigma^*) = a_0 I_1 + J_2^{1/2}$,

$$a_0 = \frac{\sin \phi}{\sqrt{9 + 3 \sin^2 \phi}},$$

$$I_1 = \sigma_x^* J_2 = \frac{1}{3} (\sigma_1^*)^2,$$

in which $\phi$ is the internal friction angle, $I_1$ is the first invariant of stress tensor, $J_2$ is the second invariant of stress devi- ation, $\sigma_1$ is the nominal stress, and $\sigma_1^*$ is the effective stress corresponding to nominal stress.

According to generalized Hook's law,

$$\varepsilon = \frac{\sigma_1^*}{E},$$

$$\sigma_1^* = \frac{\sigma_1}{1 - D},$$

in which $E$ is the elastic modulus of coal and rock sample.
It can be determined that the microelement strength of rock is

\[ F = \frac{\sin \varphi}{\sqrt{9 + 3 \sin^2 \varphi}} \times E \varepsilon + \frac{E \varepsilon}{\sqrt{3}} = \frac{E \varepsilon}{\sqrt{3}} \times \left( \frac{\sin \varphi}{\sqrt{3 + \sin^2 \varphi}} + 1 \right) = \left( \alpha_0 + \frac{1}{\sqrt{3}} \right) \times E \varepsilon. \] (13)

4.3. Intelligent Statistical Model of Coal Rock Damage Response Rate. The microelement statistical distribution is introduced into the statistical model of coal damage distribution, and the coal damage constitutive model can be obtained:

\[ \sigma_1 = E \varepsilon \left\{ 1 - \left[ \frac{\alpha_0 + (1/\sqrt{3})}{F_0} \right]^{m} \right\}. \] (14)

For the uniaxial compression stress-strain curve of coal and rock samples, the coal and rock samples are damaged at the peak value, and the conditions are met at the peak strength point \((\varepsilon_c, \sigma_c)\): (1) \(\varepsilon = \varepsilon_c, \sigma = \sigma_c\); (2) \(\varepsilon = \varepsilon_c, d_\sigma = d_c = 0\); according to the boundary conditions, it can be obtained:

\[ F_0 \left( \alpha_0 + \frac{1}{\sqrt{3}} \right) E \varepsilon_c \left( m + 1 \right)^{1/m}, \]

\[ m = \frac{\sigma_c}{E \varepsilon_c - \sigma_c}. \] (15)

Combining the two, we can get

\[ \sigma = E \varepsilon \left\{ 1 - \frac{1}{m + 1} \left( \frac{\varepsilon}{\varepsilon_c} \right)^m \right\}. \] (16)

The damage constitutive models of coal and rock samples with different water content are obtained by combining the functional relationships between peak strength, peak strain, elastic modulus, and water content of coal and rock samples, respectively, obtained above:

\[ \sigma = \left[ 3.6 e^{-0.177x} + \left( \frac{(\sigma_c e^{0.177x} - 3.6\varepsilon_c)}{\varepsilon_c^{(3.6 e^{-0.177x} - 3.6\varepsilon_c})} \right) \varepsilon_c \right]. \] (17)

4.4. Popularization and Application of Calibration Rate Response Law Based on the Elastic Modulus. The theory of elasticity is the theoretical basis for describing the constitutive model of rock. Hooke’s law proposes that for isotropic linear elastic materials, the number of independent elastic constants is reduced to two, that is, only two elastic parameters are independent. Any combination of two elastic parameters can be used to describe the elastic characteristics of isotropic materials. As a nonideal material, the deformation behavior of rock is affected by elasticity, plasticity, and viscosity. In this paper, the borehole elastic modulus instrument widely used is introduced, and the field research environment is regarded as the static mechanical environment. To describe the change process of elastic modulus, it is assumed that the rock sample is an anisotropic material. For the ideal material, there is no obvious difference between the elastic modulus obtained by the indoor small-scale test and the in situ test. Based on this, to obtain the response law of the in situ test rate based on the elastic modulus benchmark, the borehole elastic modulus instrument is used to test the in situ elastic modulus.

The borehole elastic modulus instrument (HX-JTM-01J) used in the test consists of the following 8 parts (Figure 9): displacement sensor, piezometer, oil reservoir, drill pipe joint, bearing plate, bearing block, oil pressure pump, and industrial computer.

The implementation process of the field in situ test is as follows:

1. Place the borehole elastic modulus instrument to the required depth of drilling, and start the test after confirming the direction of the loading plate. First, apply a certain pressure to make the loading plate bear the hole wall. This pressure value is the nominal zero pressure of the test, and then, record the initial value of the displacement sensor.

2. The maximum pressure shall be determined according to the rock mass strength and engineering design requirements. The classification adopts the following mode: 0-3.5-5-10-15-20-25-30-35-40-45-50-55-60 MPa

3. Pressurize step by step through the oil pump. After each pressurization, read immediately after the displacement and pressure are stable, and then, conduct the next pressurization.

4. After one test point is completed, the pressure shall be reduced to zero and maintained for some time so that the reducing plate of the drilling elastic modulus instrument returns to the minimum size and moves to the next test point.

Figure 9: Composition of borehole elastic modulus instrument.
(5) Sort out the data and draw the relationship curve between pressure and radial deformation

(6) Calculation of elastic modulus of the rock mass

Based on the elastic modulus of rock mass calculated above, the stress-strain constitutive model of the research object is reduced by combining with the rate-response statistical model of coal rock damage obtained in the previous study. Finally, the strength characteristics related to lithology are quantitatively characterized, and the field elastic modulus rate response law based on the indoor elastic modulus reference value is comprehensively analyzed.

5. Intelligent Prediction of Water- Conducting Fractured Zone Height Based on Elastic Modulus Calibration Rate Response

Most of the coal mines in the Ningdong mining area are resource-integrated mines, and there are problems such as unclear hydrogeological conditions. There is much harmful groundwater with high salinity and high acidity in the stratum, which poses a great threat to the mine [29–31]. Therefore, economic and accurate prediction of the height of the water-conducting fractured zone is an important measure to realize the safe-efficient production of coal and environmental governance in the Ningdong mining area.

5.1. Selection of Prediction Algorithm. The PSO is a population intelligence optimization algorithm [32], which updates the position and velocity of the particles through continuous iteration to find the optimal solution. Related scholars established SVR to solve the regression problem of function estimation [33]. The principle is to map the nonlinear problem in low-dimensional space to the linear problem in high-dimensional space by the kernel function.

The prediction of the height of the water-conducting fractured zone has the characteristics of small samples and nonlinearity, which is in line with the field of SVR. The penalty coefficient C avoids underfitting or overfitting by controlling the error range. The kernel parameter \( g \) controls the distribution of data, which in turn affects the speed of training and prediction. The introduction of reasonable \( C \) and \( g \) can effectively solve the problem of random mapping in high dimensions so that the SVR algorithm has higher prediction accuracy and generalization performance [34]. The nonlinear data is transformed into linear data by introducing the kernel function \( K \), and then, after processing, the regression function is obtained:

\[
f(x) = \sum_{i=1}^{n}(a_i - a_i^*)K(x, x_i) + b.
\]

In the formula, \( a \) is the Lagrange multiplier.

Therefore, using the PSO algorithm to optimize the SVR parameters can make the model converge faster and improve the accuracy of the model.

5.2. Predictive Model Construction. Constructing the height prediction model of water-conducting fractured zone based on the PSO-SVR mainly includes three steps (Figure 10): (1) inputting the height sample data, (2) PSO parameter optimization, and (3) SVR network training and testing.

5.2.1. The Input of Sample Data. Overburden failure is a nonlinear mechanical behavior under the combined action of stope geological characteristics, mining conditions, and stress environment. We collected the relevant parameters and measured values of the water-conducting fractured zone of 18 groups of mines under similar conditions [35, 36] (Table 2). The influencing parameters of the height of the water-conducting fissure zone \( y \) include the mining depth of the working face \( (m, x_1) \), inclination angle of the coal seam \( (\beta, x_2) \), thickness of the coal seam \( (m, x_3) \), hardness of the coal seam (hard coal: Platts coefficient is greater than 1; soft coal: Platts coefficient is less than 1; \( x_4 \) takes values 0.8 and 0.4, respectively), rock structure (parameter data refer to literature [37]; roof lithology structure is divided into hard-hard type, soft-hard type, hard-soft type, and weak-soft type, respectively, taking 1, 0.75, 0.50, and 0.25, \( x_5 \)), mining thickness \( (m, x_6) \), working face slope length \( (m, x_7) \), and roof rock elastic modulus \( (MPa, x_8) \).

Because the numerical value of each factor in Table 1 differs greatly, so first normalize each parameter, and the processed data are shown in Table 3.

\[
f(x_i) = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}}.
\]
<table>
<thead>
<tr>
<th>Serial number</th>
<th>Sample properties</th>
<th>Mining depth (m)</th>
<th>Dip angle (°)</th>
<th>Coal seam thickness (m)</th>
<th>Hardness</th>
<th>Overburden structure</th>
<th>Mining thickness (m)</th>
<th>Inclined length of working face (m)</th>
<th>Elastic modulus (MPa)</th>
<th>Measured value of fracture zone (m)</th>
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<td>Elastic modulus (MPa)</td>
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<td>-0.67</td>
<td>0.67</td>
<td>0.31</td>
<td>0.20</td>
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</tr>
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</table>
In the formula, \( f(x_i) \) is the normalized data, \( i = 1, \cdots, n \), \( n \) is the number of data, and \( x_{\text{max}}, x_{\text{min}} \) are the maximum and minimum values of each data.

5.2.2. Optimization of PSO Parameters and SVR Network Training. We call MATLAB’s LibSVM-Faruto Ultimate toolbox and use the particle swarm optimization algorithm to optimize the parameters of \( C \) and \( g \). The optimal solutions for \( C \) and \( g \) are 28.43 and 0.47. Substitute it into the SVR regression model and use the first 15 sets of samples in Table 2 for training to determine the training predicted value of the sample and compare with the value of the empirical formula (Table 4, Figure 11).

It can be seen from Table 2 that \( R^2 \) and RMSE of the predicted value of the height of the water-conducting fractured zone based on the PSO-SVR model are 0.93 and 4.51, respectively. \( R^2 \) and RMSE of the predicted value of the empirical formula are 0.73 and 20.04, respectively. The model training results show that \( R^2 \) based on the predicted value of the PSO-SVR model is 27.4% higher than that of the empirical formula, and RMSE is 77.5% lower.

5.2.3. Detection of the PSO-SVR Prediction Model. Test and analyze the prediction results of the PSO-SVR model through the last three groups of samples in Table 2, and compare them with the predicted values of the empirical formula (Table 5, Figure 12). It can be seen from Table 5 that \( R^2 \) and RMSE of the predicted height of the water-conducting fractured zone based on the PSO-SVR model are 0.84 and 2.44, respectively. \( R^2 \) and RMSE of the empirical formula are 0.71 and 33.65, respectively. \( R^2 \) of the predicted value based on the PSO-SVR model is 18.3% higher than that of the empirical formula, and RMSE is 92.7% lower, which verifies the scientificity of the PSO-SVR model constructed in this section.

5.3. Application of Height Prediction Model of the Water- Conducting Fractured Zone. We used the PSO-SVR model to predict the height of the water-conducting fractured zone in the Meihuajing coal mine of Ningdong mining area. The prediction result is 71.8 m and the crack production ratio is 18.41 times, respectively (Table 6).

The papers study [38, 39] the height of the water-conducting fractured zone in the Meihuajing coal mine using field measurement, empirical formula, and numerical simulation. The heights of water-conducting fractured zones obtained in the study are 71 m, 49.48 m, and 73 m, respectively, and the fracture mining ratio is 18.2 times, 12.69 times, and 18.72 times, respectively (Table 7).

The results show that the multiparameter PSO-SVR model based on elastic modulus is very close to the measured value. It can be widely used to predict the height of the water-conducting fractured zone in the Ningdong mining area.

### Table 4: Comparison of prediction accuracy and error in the network training stage.

<table>
<thead>
<tr>
<th>Model</th>
<th>( R^2 )</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO-SVR</td>
<td>0.93</td>
<td>4.51</td>
</tr>
<tr>
<td>Empirical formula</td>
<td>0.73</td>
<td>20.04</td>
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</tbody>
</table>

### Table 5: Comparison of prediction accuracy and error in the model detection stage.

<table>
<thead>
<tr>
<th>Model</th>
<th>( R^2 )</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>PSO-SVR</td>
<td>0.84</td>
<td>2.44</td>
</tr>
<tr>
<td>Empirical formula</td>
<td>0.71</td>
<td>33.65</td>
</tr>
</tbody>
</table>

![Figure 11: Comparison of the height of water-conducting fractured zone in the network training stage.](image1.png)

![Figure 12: Comparison of the height of water-conducting fractured zone in the model detection stage.](image2.png)
Table 6: Height prediction of the water-conducting fractured zone with the PSO-SVR model.

<table>
<thead>
<tr>
<th>Sample properties</th>
<th>Mining depth (m)</th>
<th>Angle (°)</th>
<th>Coal thickness (m)</th>
<th>Hardness</th>
<th>Overburden structure</th>
<th>Mining thickness (m)</th>
<th>Inclined length of working face (m)</th>
<th>Elastic modulus (MPa)</th>
<th>Predictive value (m)</th>
<th>Crack production ratio</th>
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</thead>
<tbody>
<tr>
<td>Meihuajing coal mine</td>
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<td>0.8</td>
<td>0.75</td>
<td>3.9</td>
<td>221</td>
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</table>
6. Conclusions

Although advanced calculation methods such as big data have been introduced into the existing research on the water-conducting fractured zone, there is still a certain error between it and the field’s real value. To solve the above problems, the following conclusions are obtained through research:

(1) To further clarify the distribution law of water-conducting fractured zone in arid and semiarid mining areas, the Meihuajing coal mine is selected as the engineering background, and the strength deterioration law of coal and rock mass under water-rock interaction is revealed from the engineering scale to the laboratory scale, to provide a theoretical basis for accurately obtaining the response damage model of coal and rock mass under different water states.

(2) Through the laboratory test, it is found that the peak strength and peak strain of test specimens show a linear negative function relationship with water content, and the elastic modulus of the test specimen shows a negative exponential function relationship with water content. The reason is that the water molecules in the fracture weaken the cohesion between fracture particles, soften the coal rock samples, and reduce the mechanical properties. Therefore, the increase of water content can effectively weaken the mechanical properties of test specimens and further reduce the peak strength and elastic modulus of the test specimens. The uniaxial compression failure modes of the test specimens under different water content are shear forms, and obvious shear cracks appear after the failure of test specimens. Based on this, the response damage model of coal rock ratio in different water content states is proposed.

(3) Based on the principle of cross-scale elastic modulus calibration, the strength characteristics related to lithology are quantitatively characterized by relying on the intelligent statistical model of rate response coal and rock damage. At the same time, using the research method of PSO-SVR, a height prediction model of water-conducting fractured zone based on the measured elastic modulus is proposed. The comparative analysis between the predicted value of the PSO-SVR model and the empirical formula is carried out. $R^2$ of the predicted value of the PSO-SVR model is 18.3% higher than that of the empirical formula, and RMSE is 92.7% lower, which significantly improves the prediction accuracy of the height of the water-conducting fractured zone.

### Table 7: Comparative analysis of development height of fracture zone.

<table>
<thead>
<tr>
<th>Sample properties</th>
<th>Measured value (m)</th>
<th>Crack production ratio</th>
<th>Testing method</th>
<th>Empirical formula (m)</th>
<th>Crack production ratio</th>
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<td>PSO-SVR</td>
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<td>18.72</td>
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</tbody>
</table>

### Data Availability

All data reported in this study are available upon request by contact with the corresponding author, and the author guarantees the repeatability and effectiveness of all data in this paper.

### Conflicts of Interest

No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication.

### Acknowledgments

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### References


