Research Article

Intelligent Parameter Inversion of Fractional-Order Model Based on BP Neural Network

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To explore creep parameters and creep characteristics of salt rock, an Ansys numerical model of salt rock sample was established by using fractional creep constitutive model of salt rock, and an orthogonal test scheme was designed based on uniaxial compression test of salt rock samples. A large number of training data were obtained by combining the numerical model with the experimental scheme, and the model parameters were inverted by using the BP neural network. The model parameters are used for forwarding calculation, and the results are in good agreement with the measured strain data. This shows that the model parameter inversion method proposed in this paper can obtain reasonable parameter values and then accurately predict the creep behaviour of salt rock, which provides a good technical basis for related engineering practice and scientific research in the future.

1. Introduction

With the development of world industry, the demand for oil and gas energy is growing rapidly. In recent years, many scholars have carried out a lot of research on the key technical problems of oil and gas development and achieved very fruitful results [1–9]. With the exploration and exploitation of natural gas increasing year by year, the peak shaving capacity of the pipeline network in China has not reached safety expectations. Due to its good mechanical properties [10–12], salt rock is often used as a good reservoir of oil and gas resources in recent years. The surrounding rock of the salt rock cavity will be deformed by long-term geostress during operation, which seriously affects the oil and gas storage effect and the service life of the salt cavity. Therefore, the material parameters of salt rock are the basis for studying the long-term mechanical behaviour of salt rock, and obtaining accurate material parameters is helpful to promote the safe and efficient utilization of salt caverns, which is of great significance to the development of energy storage. Therefore, this paper considers the inversion method of salt rock material parameters based on the constitutive model.

The inversion analysis method is an important mathematical method in natural science, which has been widely used in many fields such as material nondestructive testing, crop cultivation, environmental governance, and oil and gas development [13–17]. The traditional inversion method often combines the finite element method (FEM) with the optimization method and simplifies the inversion problem into the minimization of the square sum function in mathematical programming [18, 19]. In the field of geotechnical engineering, the relationship between deformation and failure of rock and material parameters under certain load conditions is studied by laboratory tests, and the corresponding constitutive model is established. Experimental data and complex mathematical methods realize the inversion of parameters. For example, Bosch et al. [20] established a general formula for inversion of seismic data under logging constraints based on petrophysical and geological statistical models and obtained the physical parameters of surrounding rock of oil and gas reservoirs with the help of logging data. Bachrach [21] used rock physics, stochastic modelling, and Bayesian estimation theory to jointly inverse porosity and saturation and obtained the saturation and porosity map of
the expected sand-producing layer. Grana [22] established the linearized analytical formula of rock-physical relationship and derived the Bayesian rock-physical inversion formula under the Gaussian assumption of the prior distribution of the model. Yang [23] also established the quantitative relationship between physical properties and elastic parameters of sand-mudstone reservoirs and realized parameter inversion using complex mathematical methods.

Although the traditional parameter inversion method is relatively straightforward, the relationship between rock deformation and material parameters is complex in actual production. If the complex constitutive model is selected for parameter inversion, the inversion process will be too long. If the constitutive model with a simple structure is selected for inversion, the accuracy will be greatly reduced [24, 25]. Therefore, the fractional differential model is considered in this paper. The concept of fractional calculus was first proposed by Leibniz and L'Hospital in 1695. Because of its good properties, fractional differential operators have a good effect in describing various materials with memory and hereditary properties, so they have been widely applied in many engineering fields [26–34]. In terms of describing the mechanical properties of rocks and other materials, the application of fractional calculus has also achieved good results. For example, Zhou [35] proposed a fraction-order creep model, which can well describe the stress, strain, and long-term behaviour of salt rocks. Wu et al. [36–39] established a new creep model based on the short-term memory variable fraction-order theory. Among these models, a fractional-order model can well reflect the nonlinear characteristics of the accelerated creep stage of salt rock, and its form is simple. The model structure is shown in Equation (1) and Figure 1. The model is composed of three parts in series: transient creep represented by Hooke body, initial creep and steady-state creep characteristic represented by Abel dashpot, and accelerated creep characteristic represented by fractional-order nonlinear dashpot element with strain triggering. This model involves five model parameters, and these parameters, respectively, represent the physical properties of the three components that make up the model.

\[
\varepsilon(t) = \begin{cases} 
\frac{\sigma}{E_0} + \frac{\sigma}{\eta_0} \frac{\mu^\beta}{\Gamma(\beta + 1)}, & (t < t_0), \\
\frac{\sigma}{E_0} + \frac{\sigma}{\eta_0} \frac{\mu^\beta}{\Gamma(\beta + 1)} + \frac{\sigma}{\eta_1} \frac{(t - t_0)^\gamma}{\Gamma(\gamma + 1)}, & (t > t_0).
\end{cases}
\]

(1)

Although this model has many advantages, it is not easy to obtain the model parameters. Therefore, this paper considers the combination of experiments, numerical simulation, and neural networks. And based on experiments, a large number of training data are obtained through numerical models. Finally, the parameters of the fractional-order model are retrieved by using a trained neural network.

### 2. Test Materials and Test Process

#### 2.1. Test Process

The salt rock samples were taken from large oil and gas reservoirs under construction or in operation in China. The specific experimental steps are as follows: after the standard test specimen is prepared and installed, the initial loading stress is set to 14 MPa. After the loading stress is applied, the strain at this moment is immediately recorded as the initial transient strain. Since the strain rate is fast at the beginning and the strain value varies greatly, the strain value should be recorded every 5-30 minutes. Then, the strain recording interval is reduced to 3-6 hours as the strain rate slows down. Subsequently, the stress of each stage was increased by 2 MPa, and the loading time of each stage was 300-400 h. The test was not stopped until the specimen was destroyed. The specific experimental details are shown in Figure 2.

#### 2.2. Analysis of Test Results

The following figure shows the uniaxial compression creep curve of the salt rock specimens under different coaxial stress. As shown in Figure 3, at the beginning of the test, the specimens experienced a relatively noticeable initial creep and then entered a relatively stable stage. The strain remained within a certain range, and there was no big fluctuation. But when the experiment was carried out around 2500 h and the loading stress was 16 MPa, the creep rate of the specimen increased significantly, and the creep velocity of the specimen exhibited prominent nonlinear characteristics when the loading stress was 22 MPa. It was evident that the salt rock specimen experienced steady creep and accelerated creep during the experiment.

We can also see from the figure that at 22 MPa, when the loading time is about 230 h, the rock salt specimen begins to enter the accelerated creep stage. Therefore, the creep data when the loading stress is 22 MPa is selected as the parameter inversion data.

### 3. Parameter Inversion Step

#### 3.1. BP Neural Network

In recent years, neural networks have been widely used in parameter inversion of engineering materials and achieved good results [40–47]. The BP neural network is a multilayer feedforward neural network trained by error backpropagation. It has a good self-organizing learning ability. It can realize arbitrary nonlinear mapping from input to output. The specific situation is shown in Figure 4.
As shown in the figure, the input layer has $m$ neuron nodes; $X_1, X_2, \cdots X_m$ is the input vector. We can take any known experimental parameter as an input vector; the hidden layer has $n$ neuron nodes; $W_{mn}$ and $W_{no}$ are the weights corresponding to the input layer to the hidden layer and the hidden layer to the input layer, respectively ($i = 1, 2, 3, \cdots m, j = 1, 2, 3 \cdots n, k = 1, 2, 3 \cdots O$); $z_1, z_2 \cdots z_O$ is the output vector; these are the model parameters to be inverted in this paper. This structure can obtain the corresponding strain output value through the hidden layer after the input of several groups of stress, time, model parameters, and other known conditions. The output value was compared with the actual measured rock salt specimen strain, and the error was fed back. The whole neural network uses the error to adjust the weight of each information transmission process so that the whole model can be improved in the progressive training, and the number of neurons in the hidden layer can also be changed artificially to achieve a better fitting effect. When the fitting effect reaches a certain degree, the network can be used to predict the strain of the salt rock specimen under certain conditions. In turn, the known test conditions such as strain and time load can be taken as the input layer data, and the model parameters to be solved can be taken as the required output layer data. After proper training, parameter inversion can be realized.

3.2. Establishment of the Calculation Model. A cylinder model with the same size and essential mechanical characteristics as the salt rock sample was established in Ansys, as shown in Figure 5. The number of elements and nodes of the model is 10000 and 1551, respectively. Fixed constraints were adopted on the bottom surface of the model, normal constraints were adopted on the sides, and a uniform load with a strength of 22 MPa was set on the top surface. UPFS is used to import the fractional-order constitutive model into the model; this calculation model will be used to calculate the axial strain of the salt rock specimen in the following text.

3.3. Construction of Parameter Calculation Scheme. According to the equilibrium dispersion characteristic of orthogonal experimental design, parameters of the nonaccelerated creep stage were inverted by using the orthogonal design method, and the three creep parameters of the fractional-order model were taken as design parameters [48, 49]. Refer to the test and inversion values of the salt rock creep parameters given in the existing literature and take five levels for
each parameter through specific trial calculation [50, 51], as shown in Table 1. According to the orthogonal design table, 25 groups of calculated parameter combination schemes were constructed, as shown in Table 2.

By inputting these experimental schemes into the finite element model for calculation, multiple sets of inversion data can be obtained, which can be used as the test data of the neural network.
4. BP Neural Network Training and Result Analysis

4.1. BP Neural Network Setting. According to the experimental scheme in the table and based on the experimental data, strain data were calculated according to the finite element model, and some data are shown in Figure 6. Data such as time, strain, load, and model parameters were summarized to obtain 1250 sets of data. The time, strain, and load data are taken as the input layer data of the neural network, and the model parameters to be inverted are taken as the output layer data. Then, we use Mathwork for neural network training and basic setup. First, the three-layer feedforward neural network is established: the number of nodes in the input layer is set as 3; the Sigmoid function of 8 nodes is adopted in the second layer; the output layer of the third layer is set as the Erf function of 3 nodes. The initial number of hidden layers was set to 8, and then, the parameters such as learning rate, batch number, and maximum iteration times were set successively. The data was used to conduct iterative training on the established neural network, and the network parameters were adjusted according to the training effect until the neural network with a good training effect was obtained. Finally, the experimental data are input into the trained neural network, and the output layer data obtained are the parameters to be inverted, as shown in Table 3.

4.2. BP Neural Network Training and Result Analysis. By substituting the creep parameters obtained by inversion in Table 3 into the model for forwarding calculation, the strain data of rock salt specimens at each time when the loading stress is 22 MPa can be obtained. We compared these data with the experimental measured data, as shown in Figure 7. It can be seen from the figure that the calculated values of salt rock strain obtained by parameter inversion are quite consistent with the measured values. Moreover, this method can not only retrieve the creep parameters in the steady-state stage of salt rock but also accurately retrieve the parameters in the accelerated creep stage. The specific parameter values are shown in Table 4. It can be seen that the derivative order of Abel dashpot obtained by inversion is less than 1, and the derivative order of fractional nonlinear dashpot is between 1 and 2, which is also consistent with the actual situation. This shows that the neural network and finite element model can be used to carry out parameter inversion of fractional-order model parameters and then provide guidance for engineering practice.

5. Conclusion

In this paper, based on the measured data in the experiment, a large number of training data are obtained by using the experimental scheme and finite element numerical model, and the neural network is trained by using the data to realize the parameter inversion of the fractional-order model. The study’s main conclusions are as follows:

(1) The inversion results are in good agreement with the actual test data, which indicates the feasibility and accuracy of the inversion method are proposed in this paper. This method lays a specific technical foundation for the further application of fractional order theory.

(2) The idea of orthogonal design is used to design the test plan. The orthogonal design method has a certain degree of uniformity, can make full use of the experimental data, improve the inversion effect, and provide high-quality training data for the neural network.

(3) The intelligent parameter inversion technology can solve the problem that it is difficult to accurately obtain the parameters of the salt rock model in the case of insufficient field test data and difficult sampling of rock samples. The neural network selected in this paper is relatively basic and can be combined with more complex intelligent algorithms in the future to achieve better inversion results and provide a scientific basis for revealing the mechanical behaviour law of salt rock.

Data Availability

All the data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declared that they have no conflicts of interest to this work. We declare that we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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