Neural Net Expansion Model for Fissured Strong Expansive Soil

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ABSTRACT: Fissured strong expansive soil swelling behavior is complicated. In this paper, considering the typical filling fissures of strong expansive soils, fissure rate K_r was given as a fissure content quantitative indicator. A prediction model was developed for the prediction of swelling effect on a fissured strong expansive soil using BP neural network approach, the gradient descent and the conjugate gradient algorithm methods were adopted. The actual test and predicted results of the two algorithms network showed high degree of similarity. The BP neural network model described by fissure rate, dry density, initial moisture content and overlying load can meet the precision requirements. The conjugate gradient method when compared with the gradient descent method, has a significantly improved calculation efficiency, the convergence rate is about 30 times lesser than the latter, therefore, conjugate gradient algorithm BP network prediction model for swelling in the actual engineering calculation has obvious advantages.

1. INTRODUCTION

Due to the unique mineral composition and structural characteristics of expansive soil, it shows mutual soil-water relationship, with the penetration of moisture, soil moisture increase, and water molecules gradually enter between clay sheets within the structure, leading to the release of large amount of stress, prompting soil volume to expands, i.e. swelling of expansive soil.

Expansive soil swelling effect give rise to the main factors of expansive soil causing geologic disasters, it is affected by the influence of soil fissure, compactness, moisture content, and various environmental factors caused by changed hydrological conditions [1–3]. Based on the South-to-North Water Transfer Project geological survey work, on strong expansive soil macro-structure, the most characteristic feature is extremely developed fissure, and its large amounts of filling material, swelling effect is very significant [4–7]. There was not a good quantitative description method for fissure development. Fissured strong expansive soil has significant impact during channel design and construction. In order to research on expansive soil swelling and contraction effect, established expansive soil multiple factors swelling model for disaster prevention and engineering construction, which has significant importance.

Artificial neutral network tool have a strong non-linear massive parallel processing capabilities, it become an effective way to solve many complex non-determined problems [8]. Recently, this theory and technology has been applied in geotechnical engineering for rock deformation and damage [9–12], rock seepage characteristics [13], soil strength characteristics [14–15] and rock subtle concept structure [16–17].

In this paper, based on field research, the method to quantify filling fissure of strong expansive soil will be determine, fissure quantitative indicator will be established, by developing remodeling strong expansive soil expansion test, to obtain the expansion law for fissured expansive soil. The use of BP neural network is employed to carry out intelligent prediction of the non-linear relationship between strong expansive soil swelling rate and fissure rate, dry density, the initial moisture content and the overlying load through established fissured strong expansive soil BP network swelling model.

2. FISSURE CHARACTERISTICS AND QUANTITATIVE GENERALIZATION PATTERN

Fissures of strong expansive soil are basically filled (see Figure 1). Due to the occurrence of strong expan-

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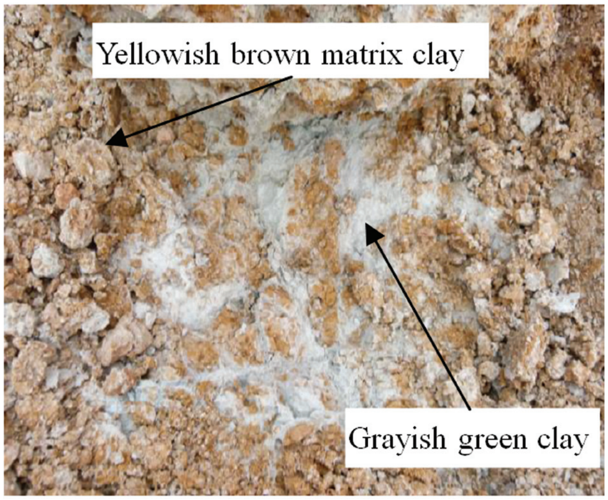


Figure 1. *Strong expansive soil filling fissure.*

sive soil at depth generally up to 15 m or more, in such a high overburden stress conditions, fissure often do not exist in the normal form of having gaps between matrix, instead of being filled with gray-grayish green cohesive soil, which has high content of clay particles and hydrophilic mineral. These filling materials form in the process of migration of groundwater in cracks, during which ion exchange effects or mineral deposition effects happen with clay minerals such as montmorillonite and illite in strong expansive soil. The filling clay soil is very fine, and the natural moisture content is generally high.

Filling material network form irregular morphology, vertical and horizontal alternating distribution in the soil, filling thickness is 2~5 mm, film-like or lenticular, partially, the thickness is 2 mm or less and more than 10 mm.

As a result of the frequent activities of the Nanyang expansive soil slope soil groundwater, most of the fissures are filled with grayish green clay soil, the rest fissure filling material are Calcium and Ferromanganese matter, etc. with very few non filled fissure.

Research shows that, weak expansive soil grayish green clay filling fissures accounted for fissure total amount of 64.3%~83.9%. In middle expansive soil region, grayish green clay filling fissure has vertical zonation characteristics, at depth within 6 m accounted for about 80%, and strong expansive soil depths are relatively high, grayish green filling fissure development is more significant, accounting for total amount of fissure for more than 90%.

As a result, considering the strong expansive soil typical filling fissures, proposed filling material content to determine the extent of fissure growth, according to statistical results made the assumption of strong expansive soil fissures are completely filled with grayish green clay. Fissure rate K_r, i.e. the ratio of fissure volume and soils volume, can be indirect described as the ratio of the content of grayish green clay and the content of yellowish brown matrix clay, in order to establish strong expansive soil fissure content quantitative indicators.

3. FISSURED EXPANSIVE SOIL EXPANSION TEST

Using quantitative indicator fissure rate, the fissure can be seen as one of the key factors included in the strong expansive soil swelling deformation model. Fissured expansive soil expansion test is carried out (see Figure 2), gray filling clay in fissure surfaces were scraped from Nanyang segment, canal section TS95, TS105, TS109, as a fissure matrix, soil matrix using Nanyang segment TS106, TS95 canal slope and canal bottom yellowish brown soil, both physical property are shown in Table 1.

Based on ratio of gray and brown clay content, configured gray clay content of 35%, 50%, 65% remolded expansive soil samples respectively for indoor test, simulated fissure were respectively 35%, 50%, 65%, different fissure rate expansive soil moisture absorption swell deformation research were conducted using no load and load swelling test, for three kinds of fissure rate of soil samples, respectively conducted three dry density value (1.45, 1.50, 1.55 g/cm^3), three initial water content amount (20%, 25%, 30%), three load (0, 25, 50 kPa) conditions swelling test, analysis of strong expansive soil hygroscopic expansion deformation law and influencing factors.

Table 1. Physical Properties Index of Fissured Expansive Soil.

Type	Moisture Content, %	Density, g/cm^3	Particles (mm) Composition, %			Liquid Limit, %	Plastic Limit, %	Free Expansion, %
			< 0.05	< 0.005	< 0.002			
Fissure matrix	29.54	1.92	92	41	15	93.51	32.76	112
Soil matrix	24.87	1.93	87	30	12	55.42	27.45	68

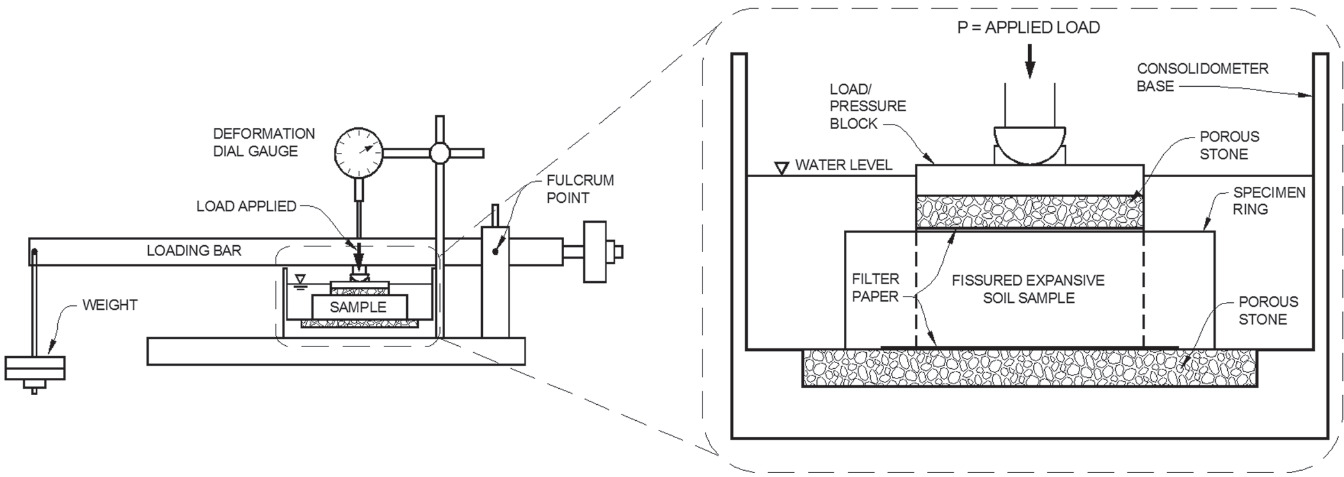


Figure 2. *Fissured expansive soil expansion test.*

4. BP NEURAL NETWORK ALGORITHMS

BP neural network is a kind of neural network model that can achieve nonlinear mapping multilayer feed-forward. Multilayered networks are capable of computing a wider range of Boolean functions than networks with a single layer of computing units. The basic three feed-forward BP neural network consists of an input layer, an output layer and a hidden layer, the topological structure is shown in Figure 3.

Through the learning samples, mapping from input layer n-dimensional Euclidean space to the output layer m-dimensional Euclidean space can be completed, which can be used for pattern recognition and interpolation, and it can approximate any nonlinear function in arbitrary precision. One hidden layer structure is generally used, for hidden layer quantity increase have no direct effect to improve precision of the network as well as enhance the network ability to express.

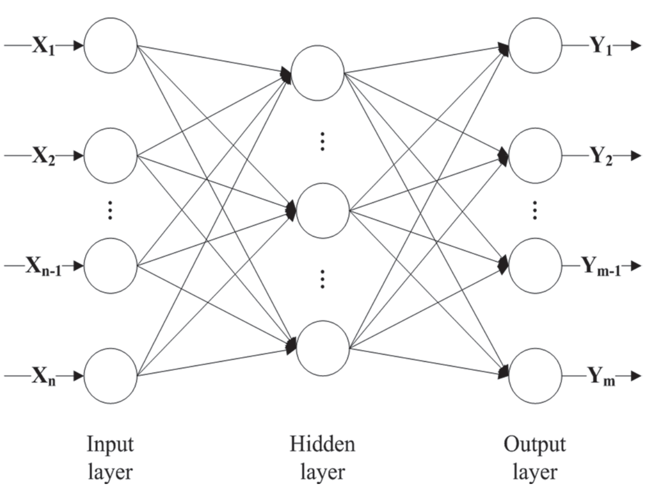


Figure 3. *BP neural network topology diagram.*

BP network study process is the process of error back propagation algorithm, through the forward calculation and the error back-propagation, gradually adjusting the connection weights, until the network error $E(k)$ reduce to the desired value, or reach the intended learning frequency.

Neurons function is normally the derivable S (sigmoid) type function [18]:

$$f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

$$f'(x) = f(x)[1 - f(x)] \tag{2}$$

Error function R is:

$$R = \frac{\Sigma(Y_{mj} - Y_j)^2}{2} \quad (j = 1, 2, \ldots, n) \tag{3}$$

Where, Y_j is the desired output; Y_{mj} is the actual output; n is the sample length.

The most widely used standard BP algorithm is gradient descent algorithm, Let k be the iteration frequency, from any given point $\vec{z}(k)$, along the negative gradient direction $\vec{s}(k)$ in which the function declines the fastest to conduct 1-dimensional search:

$$\vec{s}(k) = -\nabla f[\vec{z}(k)] \tag{4}$$

Where, $\nabla f[\vec{z}(k)]$ is the gradient vector iterative point $\vec{z}(k)$. Then the next iteration point is

$$\vec{z}(k+1) = \vec{z}(k) + \vec{a}(k)\vec{s}(k) \tag{5}$$

Where, $\vec{a}(k)$ is the optimal step size. Terminal condition of the iteration is:

$$\|\Delta\vec{z}(k)\| < \varepsilon \tag{6}$$

Conjugate gradient algorithm, by improving the search direction, using a linear combination of the gradient of the previous iteration points and the gradient of the present iteration points, obtained a new search direction, Fletcher-Reeves algorithm (Traincgf) as follows:

$$\vec{z}(k+1) = \vec{z}(k) + \vec{a}(k)\vec{s}(k) \tag{7}$$

$$\vec{s}(k+1) = -\vec{g}(k) + \beta(k)\vec{s}(k) \tag{8}$$

$$\beta(k) = \frac{[\vec{g}(k+1)]^{\mathrm{T}}\vec{g}(k+1)}{[\vec{g}(k)]^{\mathrm{T}}\vec{g}(k)} \tag{9}$$

$$\vec{g}(k) = -\nabla f[\vec{z}(k)] \tag{10}$$

Where, $\vec{s}(k)$ is the search direction, which is a set of conjugate vectors; $\vec{a}(k)$ is rep increments.

5. STRONG EXPANSIVE SOIL BP NETWORK SWELLING PREDICTION MODEL

5.1. Network Model Structure

For fissured strong expansive soil neural network swelling prediction model, using basic three feed-forward BP network, i.e. network model consists of an input layer, an output layer and a hidden layer, which guarantees high prediction accuracy. According to the network accuracy requirements and strong expansive soil swelling rate change controlled factors, the input layer includes fissure rate, dry density, the initial moisture content and the overlying load, obtained a network model input layer consisting of 4-dimensional vector components:

$$X = [K_r, \rho_d, w_0, \sigma] \tag{11}$$

i.e. fissure rate K_r (%), dry density ρ_d (g/cm^3), the initial moisture content w_0 (%), the overlying load σ (kPa) respectively are for the four input neurons. Output layer is 1-dimensional vector:

$$Y = [\delta_{ep}] \tag{12}$$

Swelling rate of expansive soils δ_{ep} (%) is the output neuron, thereby established strong expansive soil swelling prediction network model. Figure 4 is the schematic model.

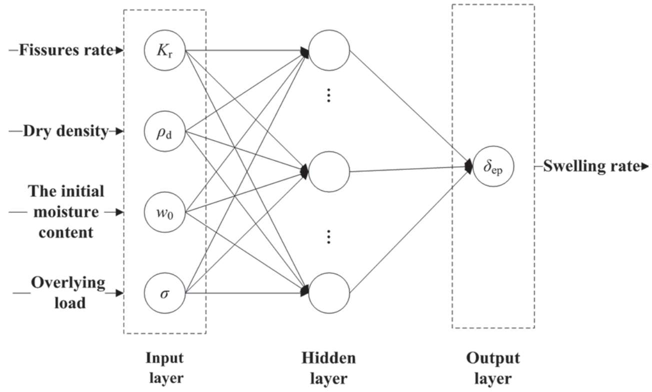


Figure 4. Strong expansive soil prediction BP network structure diagram.

5.2. Samples Data Analysis and Processing

The total number of train samples for BP neural network is 81, sample sources are laboratory test data, soil characteristics include three fissure rate (35%, 50%, 65%), three dry density (1.45, 1.50, 1.55 g/cm^3), three initial water content (20%, 25%, 30%), three load (0, 25, 50 kPa). Table 2 gives an example of train samples.

Singular sample data refer to the significant large or small sample data relative to other input sample. It can be seen from Table 2, expansive soil dry density is between 1.45~1.55 g/cm^3, its value is significantly small compared to the fissure rate, moisture content, and load expressed in percentage. Dry density, which is the singular sample data, may reduce the computational efficiency, and cause the results inability to converge during calculation. So, before the network computing, there is need to conduct normalization process for train data. An adequate normalization, not only for the network output variables but also for the input ones, previous to the training process is very important to obtain good results and to significantly reduce calculation time.

Data normalization is a process whereby target data will be limited within the specific range with the calculation requirement after the treatment through some algorithm, and transform variables to dimensionless scalars. On the one hand it can ensure the convenience

Table 1. Train Sample Illustration.

Input Layer				
K_r (%)	ρ_d (g/cm^3)	w_0 (%)	σ (kPa)	Output Layer δ_{ep} (%)
35	1.45	20	0	13.05
35	1.55	30	50	0.84
65	1.55	30	0	10.81

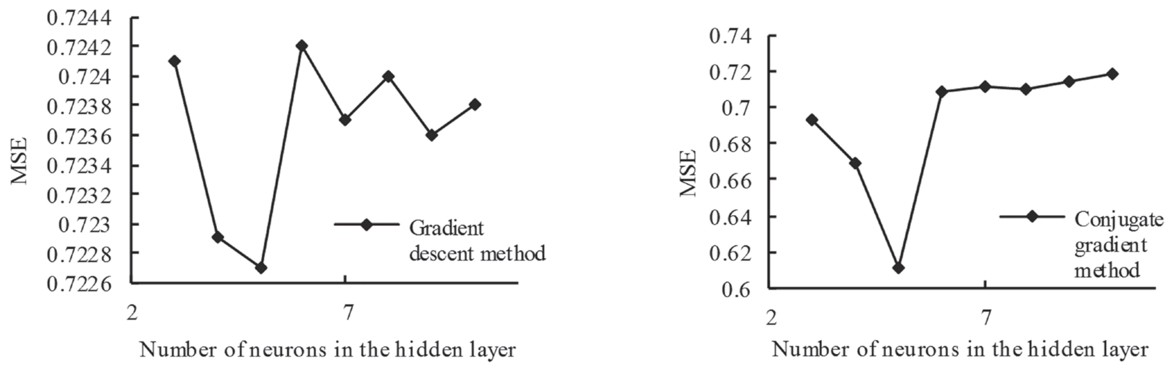


***Figure 5.** MSE of predicted results for different hidden layer neurons.*

of subsequent data processing, the other is to speed up the convergence rate. Using premnmx function, network input data and output data were normalized, the normalized data is distributed within [–1,1], eliminating the singular sample data.

Assuming that data $d=\{d_i\}$ is normalized $d'=\{d_i'\}$, it can be calculated through the formula below:

$$d_{\mathrm{i}}' = (y_{\max} - y_{\min})\frac{d_{\mathrm{i}} - d_{\min}}{d_{\max} - d_{\min}} + y_{\min} \qquad (13)$$

Where, $y_{\max} = 1$, $y_{\min} = -1$, $d_{\max}$ and $d_{\min}$ are the maximum and minimum formula data in the samples, $y_{\min} \le d_{\mathrm{i}}' \le y_{\max}$.

5.3. Network Model Parameters

Model training functions are traingdm function and traincgf function respectively, for gradient descent algorithm and conjugate gradient algorithm, hidden layer activation function is tansig function, the output layer activation function is purelin function, the maximum number of iterations is epochs = 6000, the minimum expected error setting value is goal = 0.01, learning efficiency correction weights is lr = 0.05.

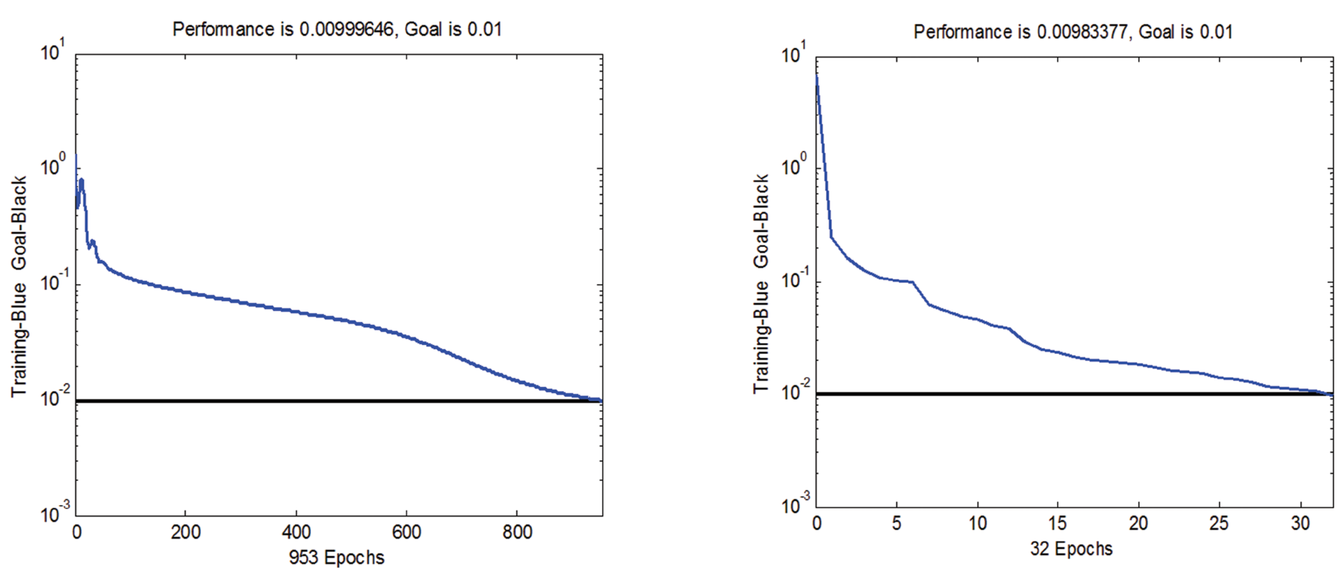
The number of hidden layer nodes complies with the accuracy and reasonableness of the entire network, generally uses spreadsheet optimization method to find the optimal solution.

Adopt MSE as an index, for predicting data and raw data corresponding point error squares and mean value:

$$\mathrm{MSE} = \mathrm{SSE}/n = \frac{1}{n}\sum_{i=1}^{n}(w_i\ \ y_i - \hat{y}_i)^2 \qquad (14)$$

The closer the MSE to 0, the better the data prediction possibility and the fitting model.

Number of neurons in the hidden layer takes 3 to



(a) (b)

***Figure 6.** Operating results for different algorithm program. (a) Gradient descent algorithm, and (b) Conjugate gradient algorithm.*

Table 3. Gradient Descent Algorithm BP Neural Network Structure Parameters.

Number of Neurons in the Hidden Layer	Hidden Layer					Output Layer		
	Weights w_1				Threshold b_1	Hidden Layer Node Number	Weights w_2	Threshold b_2
5	–-0.4091	–0.0078	0.8350	1.9573	1.6289	1	–0.7429	–0.0264
	1.7492	–0.4154	0.7599	0.4727	–1.1377	2	0.0491	
	0.2801	1.0547	0.6010	–1.5505	0.0275	3	0.0610	
	1.1448	–1.0334	1.2182	–0.8692	0.7488	4	0.0072	
	–1.0582	–0.8798	0.5686	1.3874	–2.1083	5	–0.1891	

10 respectively, adopted gradient descent and conjugate gradient algorithm, MSE of predicted results are shown in Figure 5.

For the gradient descent algorithm and conjugate gradient algorithm, when hidden layer contains 5 neurons, MSE reached its minimum at 0.7227 and 0.6117 respectively, so the network hidden layer number of neurons is set to 5.

6. NETWORK MODEL PREDICTED RESULTS ANALYSIS

Strong expansive soil network model gradient descent algorithm and conjugate gradient algorithm program operation results are shown in Figure 6.

Comparison of the two algorithms operation results, shows after 953 iterations for gradient descent algorithm, the network error is 0.00999646, less than the expected error of 0.01, while the conjugate gradient algorithm is only requires 32 iterations to achieve the desired error, thus conjugate gradient algorithm convergence rate is far higher than the gradient descent algorithm, network model structural parameters of the two algorithms are shown in Table 3 and Table 4.

Figure 7 shows the comparison of fitted values and measured values of expansive soil swelling rate calculated from the trained data. As can be seen, expansion deformation fitted values and measured values of the gradient descent algorithm and conjugate gradient algorithm were consistent, error can be controlled within a narrow range, indicating that the network model has a high fitting precision.

After the network is fully trained, to verify the accuracy of the model, a set of measured data different from training samples is selected, the results calculated through the model are shown in Figure 8.

As can be seen, for fissured strong expansive soil deformation prediction, the measured results and the prediction results are similar for the two networks of the gradient descent algorithm and the conjugate gradient algorithm, and the network model can meet the accuracy requirements. Through fissure rate, dry density, the initial moisture content and the overlying load, BP neural network can be used intelligently to predict the expansion effect of strong expansive soil. By comparing different algorithms, found that the conjugate gradient algorithm relatively gradient descent, significantly improve computational efficiency, the convergence rate of about 30 times the latter, therefore, conjugate gradient algorithm of BP network predicted model for expansion in the actual engineering calculation has obvious advantages.

7. CONCLUSION

Considering the strong expansive soil typical filling fissures, proposed filling material content to determine the extent of fissure growth, fissure rate K_r is given as

Table 4. Conjugate Gradient Algorithm BP Neural Network Model Structure Parameters.

Number of Neurons in the Hidden Layer	Hidden Layer					Output Layer		
	Weights w_1				Threshold b_1	Hidden Layer Node Number	Weights w_2	Threshold b_2
5	–0.5157	–1.0865	1.3420	–1.0923	2.0438	1	–0.0476	0.4107
	1.5204	0.8745	–0.8515	0.0430	–0.7941	2	0.1455	
	0.1425	0.0548	–0.3567	–1.8996	–1.8809	3	0.9882	
	–0.3334	1.1245	0.6279	1.7224	–0.4459	4	–0.0539	
	0.7652	0.4226	0.6090	1.6750	2.2501	5	–0.0092	

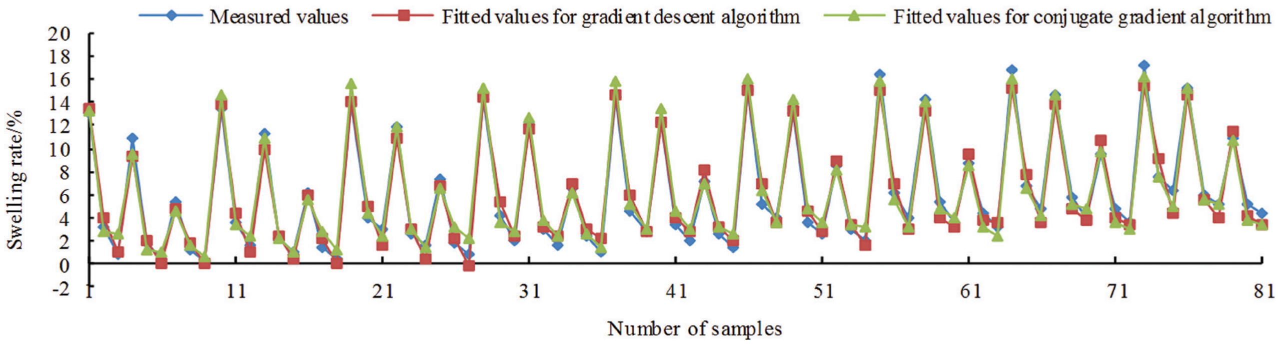


Figure 7. *BP model fitted and measured values comparison.*

a strong expansive soil fissure content quantitative indicator, which can be indirect described as the ratio of the content of grayish green clay and the content of yellowish brown matrix clay of strong expansive soil.

The back-propagation training algorithm is explained. Partial derivatives of the objective function with respect to the weight and threshold coefficients are derived.

These derivatives are valuable for an adaptation process of the considered neural network. Training and generalization of multi-layer feed-forward neural networks are discussed. Improvements of the standard back-propagation algorithm are reviewed.

For fissure expansive soil deformation prediction adopt gradient descent and the conjugate gradient algorithms, the actual test results and predicted results of the two algorithms network shows high degree of similarity. The network model described by fissure rate, dry density, initial moisture content and the overlying load, which using BP neural network intelligence for predicting strong expansive soil swelling effect, can meet the precision requirements. It is found that the conjugate gradient method when compared with the gradient descent method, has a significantly improved calculation efficiency, the convergence rate is about 30 times lesser than the latter, therefore, conjugate gradient algorithm BP network prediction model for swelling in the actual engineering calculation has obvious advantages.

8. ACKNOWLEDGEMENTS

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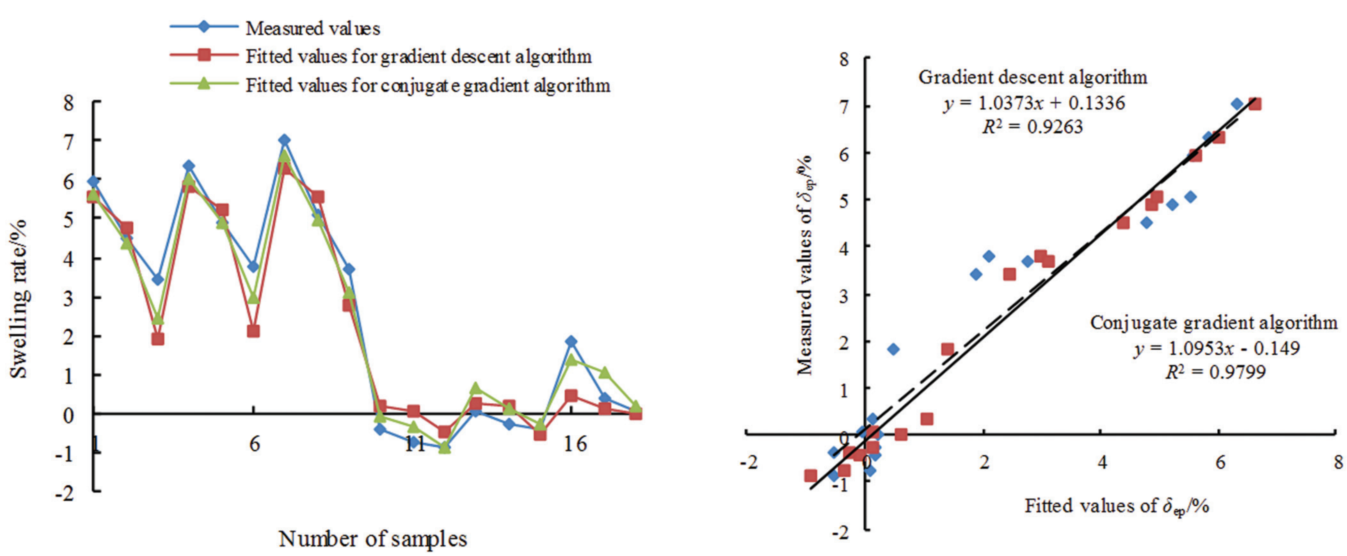

Figure 8. *Expansion model prediction results.*

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