Journal of Research in Science and Engineering (JRSE)
ISSN: 1656-1996 Volume-4, Issue-2, September 2022
DOI: 10.53469/jrse.2022.04(09).11

Application of Parameter Inversion in Tunnel Stability Analysis

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Abstract: ***Tunnel stability evaluation is of great significance for construction and operation safety, and formation physical and mechanical parameters are essential and important indicators in tunnel stability evaluation. However, in some cases, it is difficult to directly measure the physical and mechanical parameters of the formation. This paper relies on the No. 2 Dalu Tunnel of the Huanji Expressway Project, which passes through strongly weathered granite, and the exit section is a shallow-buried biased section. Some parameters are difficult to obtain. Therefore, using the deformation measurement data obtained from the tunnel construction, the PSO-SA-BP intelligent algorithm is used to invert and analyze the relevant formation physical and mechanical parameters, and the obtained inversion parameters are applied to the FLAC3D numerical simulation. The results show that the numerical simulation based on the inversion data is highly consistent with the actual deformation, which proves the practicability of the inversion method of the physical and mechanical parameters of the formation, and has certain reference significance for tunnel engineering simulation.***

Keywords: Tunnel engineering, Parameter inversion, Intelligent algorithm, Stability Analysis**.**

1. Introduction

In the Huanji Expressway project, the shallow-buried eccentric pressure section at the exit of the No. 2 tunnel on Dalu has thick breccia on the surface and strongly weathered granite underneath. The rock mass is divided into various discontinuities and even fragmented bodies. There are many cracks, the distribution of in-situ stress is complex, and it is difficult to obtain the physical and mechanical parameters of the rock and soil mass on site. The physical and mechanical parameters of the formation can be obtained more accurately from the inverse analysis of the tunnel deformation measurement data[1], and the stability evaluation based on the inversion parameters is more practical and has guiding significance for engineering construction. In recent years, due to the powerful nonlinear fitting ability of machine learning, the use of machine learning and numerical simulation to perform displacement inverse analysis to obtain formation parameters is one of the hot research directions in the geotechnical field. Many scholars use simulated annealing algorithm, genetic algorithm, particle swarm algorithm, BP neural network algorithm to inversion of geotechnical parameters[2-11]. Liu[12], Wang[13] etc. applied the inversion parameters to the tunnel stability analysis.

In this paper, an inversion model combining particle swarm algorithm, simulated annealing algorithm and BP neural network algorithm is used, and the model is used to invert the formation parameters, and the inversion parameters are applied to the stability analysis of the shallow buried bias section of the Dalu No. 2 tunnel.

2. POS-SA-BP Parameter Inversion Model

The POS-SA-BP parameter inversion model used in this paper can establish the mapping relationship between deformation information and mechanical parameters. The principle is to use particle swarm algorithm and simulated annealing algorithm to optimize the weight and threshold of BP neural network algorithm in advance., then the BP neural network algorithm further inverts to obtain the mechanical parameters of the formation.

The processing procedure of the PSO-SA-BP parameter inversion model based on the fusion of the three algorithms is shown in Figure 1.

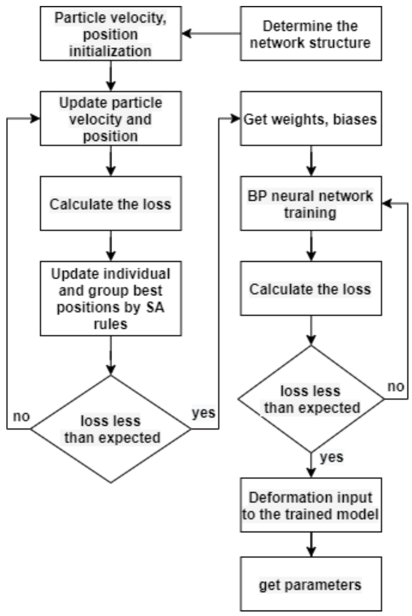


Figure 1: Processing flow of POS-SA-BP geotechnical parameter inversion model

Its mathematical expression is as follows:

$$x^{'} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

$$\begin{cases} v_w = c_0 v_w + c_1 r_1([pbest_{i_w}] - [i_w]) + c_2 r_2([gbest_{i_w}] - [i_w]) \\ i_w = i + v_w \\ v_b = c_0 v_b + c_1 r_1([pbest_{i_b}] - [i_b]) + c_2 r_2([gbest_{i_b}] - [i_b]) \\ i_b = i + v_b \end{cases} \tag{2}$$

$$[y] = f([i_w] \times [x] + [i_b]) \tag{3}$$

$$loss = \frac{\sum_{i}^{n}(y_i' - y_i)^2}{n} \tag{4}$$

$$P=\begin{cases} 1 & loss_{t+1} < loss_t \\ e^{-\frac{loss_{t+1}-loss_t}{kT}} & loss_{t+1} > loss_t \end{cases} \tag{5}$$

$$T_{t+1} = kT_t \tag{6}$$

$$\begin{cases} [y] = f([i_w]\times[x]+[i_b]) \\ [i_w]=[i_w]-\eta\dfrac{\partial loss}{\partial[i_w]} \\ [i_b]=[i_b]-\eta\dfrac{\partial loss}{\partial[i_b]} \end{cases} \tag{7}$$

where x is the input deformation data, i_w, i_b are weights and biases, v_w, v_b are the velocities of the weighted particle swarm and the biased particle swarm, y is the parameter obtained by inversion, *loss* is the difference between the inversion displacement and the actual displacement, P is the probability of accepting a better position, T is the temperature of the SA algorithm cycle.

3. Project Overview of Dalu No. 2 Tunnel

3.1 Engineering Technology Overview

The No. 2 Dalu Tunnel is located in the east of Ji'an City, Jilin Province, China, About 3km southeast of Dalu Town. It adopts a separate design, the left line clearance is 10.75×5m, the starting and ending stakes are LK209+460~LK211+525, and the tunnel length is 2065m. The road grade is a two-way four-lane expressway with a design speed of 100km/m.

3.2 Engineering Geological Conditions

Dalu No.2 tunnel is located in level IV structural unit (Taizi River concave fold fault bundle), The formation lithology is mainly composed of biotite granite, and the groundwater is mainly bedrock fissure water, dDalu No. 2 tunnel, the left side exit section spans 12.5m, the hole height is 9.6m, the slope terrain is steep, the natural slope foot is 36°, and the tunnel roof is buried in a depth of 0~17m.

The surrounding rock is mainly strongly weathered granite, which is fragmented, and partially gritty. The rock mass is extremely broken, and the joints and fissures are extremely developed, most of which are open and medium permeable. There is thick weathered soil with breccia on the surface, and the breccia content is about 60%.

3.3 Tunnel Deformation Monitoring Method and Data

The tunnel is excavated by upper and lower steps in the shallow buried bias section. Monitoring and measurement content includes surface subsidence measurement, vault crown settlement, and tunnel horizontal convergence measurement. The layout of monitoring points and monitoring data at the section K211+509 of the shallow-buried bias section are shown in Figure 2.

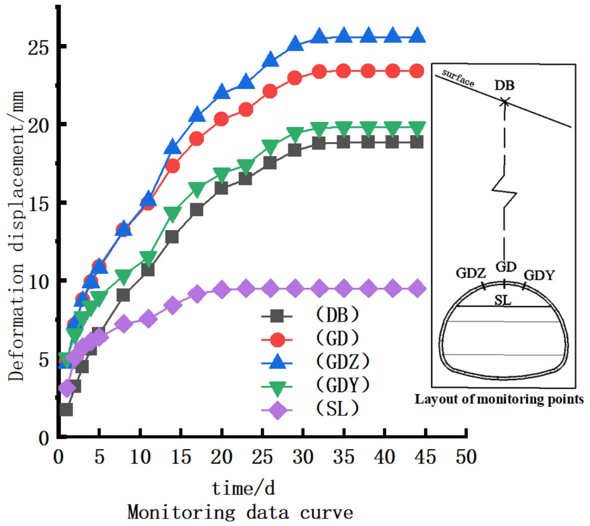


Figure 2: Monitoring point layout and monitoring curve

4. Establishment of Numerical Model and Analysis of Results

4.1 Establishment of 3D Numerical Model

The establishment of three-dimensional numerical model selects the shallow buried bias section at the left exit of No.2 road as the research object, and uses FLAC3D to conduct three-dimensional numerical simulation. The tunnel axis extends from k211 + 470 section to k211 + 520 section, the bottom boundary is 45m away from the tunnel floor, the left and right boundaries are 45m away from the tunnel side wall. Normal constraint is applied at the bottom and its surroundings, and the surface is free. The Mohr-colomb model is adopted as the constitutive model in this paper. The numerical model is shown in Figure 3.

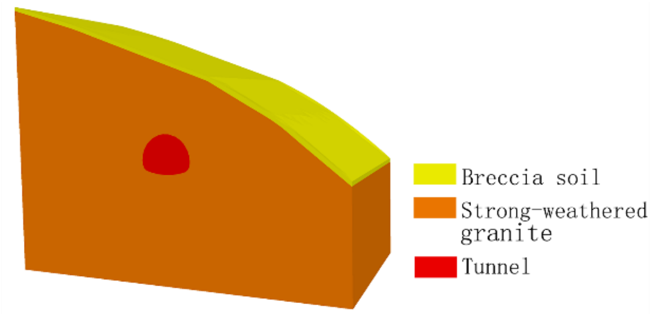


Figure 3: Numerical model of Dalu No. 2 tunnel project

The construction process of numerical simulation refers to the actual construction process: forepoling bolt support → Upper step excavation → Lower step excavation → Inverted arch excavation. The excavation shall be carried out circularly, and the excavation footage of each step is 1.5m. Support construction after the excavation stress is released for a period of time. Steel arch frame and shotcrete anchor combined support are adopted for primary lining. The strength of shotcrete is greater than 25MPa and the thickness is 26cm. The steel arch frame is calculated by the lining element according to the principle of equivalent stiffness. Cable element is adopted for anchor bolt and advance anchor bolt. Physical and mechanical parameters of primary lining are shown in Table 1.

Table 1: Mechanical parameters of the support structure

component	shotcrete	bolt	Advance bolt
Elastic modulus E/GPa	31	210	230
Poisson's ratio μ	0.2	0.3	0.3
Density ρ/(kg.m^{-3})	2800	8000	8000
Cohesion c/kPa	3000	/	/
interior friction angle φ/°	55	/	/
Thickness D/cm	26	/	/

The elastic modulus (E), Poisson's ratio (u), cohesion(c) of strongly weathered granite are selected as inversion parameters, Other parameters are measured. The formation parameters are shown in Table 2 below.

Table 2: Mechanics parameters of stratum

stratum	Breccia soil	strong-weathered granite
Elastic modulus E/MPa	6.5	100~1000
Poisson's ratio μ	0.32	0.1~0.48
Cohesion c/kPa	15	10~50
interior friction angle φ/°	20	35
Density ρ/(kg.m^{-3})	1850	2000

4.2 Establishment of Training Samples

16 groups of training samples were established through the orthogonal experiment with 3 factors and 4 levels. The tunnel deformation data and stratum parameters are brought into the model to establish the mapping relationship between deformation data and mechanical parameters. The training samples are shown in Table 3.

Table 3: Training sample

Deformation data

DB/mm	GD/mm	GDZ/mm	GDY/mm	SL/mm
7.6	9.4	10.2	8.8	3.4
15.0	15.9	16.6	15.3	10.1
4.9	5.9	6.3	5.8	2.1
33	34.1	34.9	33.5	28
7.5	8.6	9.0	8.19	3.5
11.4	14.6	16.4	13	6.1
9.7	10.2	10.7	9.9	8.6
13	14.6	16.8	8.7	9.8
3.3	4.4	5.0	3	2.7
16.5	19.3	21.1	17.4	7.3
8.8	9.3	9.5	8.9	6.1
3.1	3.8	4.2	3.4	2.4
21.3	22.6	23.7	17.68	18
8.1	8.8	9.4	8.3	5.9
20	20.8	21.4	20	17
7.1	8.6	9.5	7.6	4.1

Physical and mechanical parameters

E/Mpa	u	c/kpa
400	0.2	45
400	0.1	25
800	0.1	45
600	0.2	15
600	0.1	35
200	0.3	45
200	0.1	15
200	0.4	25
600	0.4	45
200	0.2	35
800	0.2	25
800	0.4	35
400	0.4	15
600	0.3	25
800	0.3	15
400	0.3	35

5. Results and Discussion

The *loss* in the training process of the inversion model based on the three algorithms are shown in Figure 4.

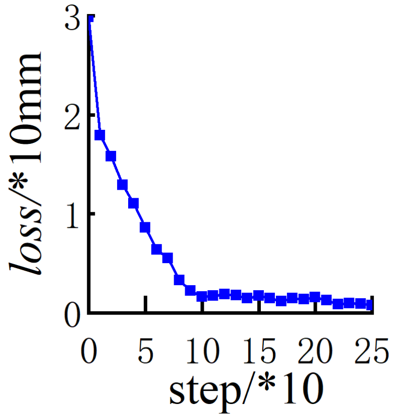


Figure 4: Loss during model iteration

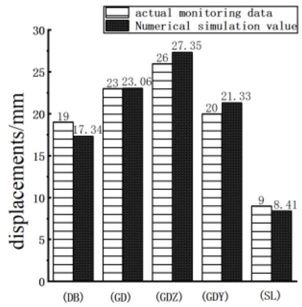
It can be seen from Figure 4 that during the model iteration process, the loss decreases continuously, from the initial 29mm to the final 7.1mm, which proves the convergence ability of the model. This means that the average to each deformation data, the error does not exceed 1.4mm, the inversion ability of the model is reliable.

The model inverses the elastic modulus, Poisson's ratio and cohesion of the strongly weathered granite according to the input actual deformation. The results are shown in Table 4.

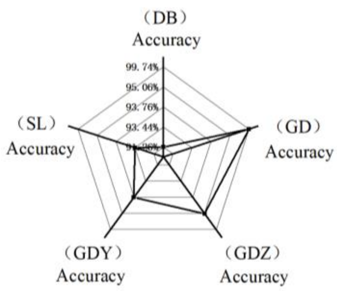
Table 3: the inversion values of stratum parameter

stratum	Inversion value		
	E/MPa	u	C/kPa
Strongly weathered granite	230	0.33	24

Bring the inversion parameters into FLAC3D for simulation. The comparison between the simulated deformation data and the measured deformation data is shown in Figure. 5.



(a) Histogram of inversion value and monitoring value



(b) Radar map of inversion value and monitoring value

Figure 4: Comparison between inversion prediction values and monitoring values

It can be seen from Figure 5 that when the inversion parameters are applied to the numerical simulation, the displacement shown is in good agreement with the monitoring value, and the accuracy is more than 91%, Among them, the accuracy of the vault (GD)and both sides of the vault (GDZ)(GDY)is the highest, and the accuracy of the surface subsidence(DB) and horizontal convergence (SL)is slightly lower. The horizontal convergence is affected by multi-directional tectonic stress, and the surface subsidence is disturbed by many factors such as the erosion of surface water flow and the change of soil moisture content caused by climate. However, the numerical simulation model does not consider relevant factors, so the accuracy of horizontal convergence and surface subsidence is slightly lower than that of the vault and both sides. It can be seen from the data that the numerical simulation based on the inversion parameters can better reflect the real situation, and it is reasonable to use the inversion parameters. The inversion parameters can be used to replace the empirical parameters for the stability analysis of the shallow buried bias section of the tunnel.

6. Conclusion

Based on the shallow buried bias section at the exit of No. 2 tunnel of Huanji expressway project, the physical and mechanical parameters of strongly weathered granite are inversed by pso-sa-bp intelligent inversion model. The inversion parameters are substituted into the numerical simulation calculation, and the simulation results are compared with the monitoring data. Through these operations, the following conclusions can be drawn:

(1) For physical and mechanical parameters that are difficult to measure in the field, the deformation monitoring data can be used for parameter inversion to obtain parameters that are more in line with the actual field.

(2) It is feasible to optimize the weights and thresholds of BP neural network algorithm in advance by using particle swarm optimization algorithm and simulated annealing algorithm. The pso-sa-bp intelligent inversion model can effectively establish the relationship between the deformation data of Dalu No. 2 tunnel and the physical and mechanical parameters of surrounding rock.

(3) The formation parameters obtained by the inversion of the PSO-SA-BP intelligent inversion model are brought into the numerical simulation. The simulated deformation is relatively close to the monitoring data, and the accuracy is above 91%. It further proves the practicality of the PSO-SA-BP intelligent inversion model

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