Limit Displacement Prediction Method for Deep Roadway

Zhiping Li [1, a], Jiancong Xu [2, b] and Jiaqing Du [3, c]

[1]China Nerin Engineering Co., Ltd., Nanchang, Jiangxi 330031, China

[2]Department of Geotechnical Engineering, Tongji University, Shanghai 200092, China

[3]Department of Civil Engineering, Shanghai Jiao Tong University, Shanghai 200240, China

[a]lzp3143@163.com

Abstract

To solve nonlinear large deformation prediction of soft rock for a coal mine deep roadway, the least squares method of support vector machine (LSSVM) was established as a prediction model for the limit displacement of deep roadway. This method was applied to limit displacement prediction and analysis of the central substation in No. 9 Coal Mine of Hebi Coal Industry, China. The support effect of the engineering area was evaluated comprehensively through a comparison between the results of the FLAC^{3D} numerical simulation and on-site monitoring values. Results show that the relative error of limit displacement obtained by the LSSVM prediction model is -3.44% for the FLAC^{3D} numerical simulation value and 8.46% for the on-site monitoring value. Thus, the prediction has great accuracy and meets engineering requirements for a deep roadway. The results have great significance for estimating the stability of deep roadway in advance, thereby providing critical guidance to ensure the stability of deep roadway and save project investment.

Keywords

Deep Roadway; Limit Displacement Prediction; Least Squares Support Vector; Numerical Simulation; Coupling Support.

1. Introduction

Supporting technology for rock stability issues in deep roadways in coal mine is currently a key program in China and is developed through a series of solving methods for engineering samples. The relationship between deformation and the influencing factors for deep surrounding rock is complex and nonlinear; it cannot be explained by traditional linear theory such that the development of a limit displacement prediction method for deep roadway has significant application. Intelligent rock mechanical technologies have been proposed for solving problems in deep roadway. Improved Verhulst model and gray effect measure theory were used to analyze destruction trends in the roof of a soft rock roadway [1]. Principal component analysis and random forest were combined to forecast roadway stability in coal mine [2]. Gray prediction model groups of surrounding soft rock deformation were established to predict surrounding rock deformation of the roof, floor, and two sides of a coal mine roadway [3]. Fuzzy mathematics theory and gray theory were combined to predict surrounding rock deformation in a deep coal mine tunnel [4]. An evolutionary neural network model was constructed to predict the thickness of loose zones around roadway [5]. However, in most cases, these techniques are costly, time consuming, and difficult to implement.

The least squares (LS) version of support vector machine (SVM) has become widely used for prediction in underground engineering. For example, the random WPSO–LSSVM model was established and applied for limit displacement prediction of large underground caverns [6–9]. Bayesian and LSSVM back-analysis techniques were combined to solve geomechanical parameter identification in slope stability [10–13], and other typical SVM analysis technique were described by[14-20]. In the present study, an LSSVM prediction model for the limit displacement in a coal mine deep roadway was established and applied for limit displacement prediction of a test roadway in No. 9 Coal Mine of Hebi Coal Industry, China. The developed limit displacement prediction model for deep roadway was verified through a comparison with the results of $FLAC^{3D}$ numerical simulation and on-site monitoring.

2. Limit Displacement Prediction Model of Deep Roadway

2.1 Principle of LSSVM [21]

SVM for classification and nonlinear function estimation, as introduced by Vapnik [22] and based on statistical learning theory, is an important methodology in the area of neural networks and nonlinear models. LSSVM was proposed by Suykens et al. [23] and is an extension of standard SVM.

Given training data $\left\{(x_i, y_i) \mid x_i \in R^n, i = 1, 2 \cdots n\right\}$

with input data x_i, output data y_i, and sample number *n*. Assuming that all training data can be fitted into the following linear function:

$$\left.\begin{aligned} y_i - wx_i - b \le \varepsilon \\ wx_i + b - y_i \le \varepsilon \end{aligned} \quad i = 1, 2, \cdots, k \right\} \tag{1}$$

one considers the following optimization problem in primal weight space

$$\min_{w,b,e} j(w,e) = \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{k=1}^{N} e_k^2 \tag{2}$$

The constraint condition is $y_k = w^T \varphi(x_k) + b + e_k$, $k = 1, \cdots, \mathrm{N}$

where $\varphi(\cdot): R^n \to R^{n_h}$ is a function that maps the input space to a higher dimensional feature space, and weight vector $w \in R^{n_h}$, error vector $e_k \in R$, and offset value $b \in R$. We define the function

$$\mathrm{L}(\mathrm{w,b,e;a}) = \mathrm{j}(\mathrm{w,e}) - \sum_{\mathrm{k=1}} \alpha_{\mathrm{k}} \left\{ \mathrm{w^T j}(\mathrm{x_k}) + \mathrm{b} + \mathrm{e_k} - \mathrm{y_k} \right\} \tag{3}$$

By using Lagrange multipliers $\alpha_k \in R$ (called support value), and eliminating w, e, we obtain the solution

$$\begin{bmatrix} 0 & l_v^T \\ l_v & \Omega + \frac{1}{\gamma} I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ y \end{bmatrix} \tag{4}$$

with $x = [x_1; \cdots; x_N]$, $y = [y_1; \cdots; y_N]$, $l_v = [1; \cdots, l], \alpha = [\alpha_1; \cdots; \alpha_N]$ and $\Omega_{k1} = \psi(x_k, x_l) = \varphi(x_k)^T \varphi(x_l), k, l = 1, \cdots, N$.

According to Mercer's condition, function ω and $\psi(\ ,\ )$ exist such that

$$\psi(x_k, x_l) = \varphi(x_k)^T \varphi(x_l) \tag{5}$$

Thus, the resulting LSSVM model for function estimation becomes

$$\mathrm{y}(x) = \sum_{k=1} \alpha_k \psi(x, x_k) + b \tag{6}$$

where α and b are the solution for (4), and $\psi(x, x_k)$ has three choices

(1) Polynomial kernel function is $\psi(x_k, x_l) = (x_k x_l + 1)^d, (d = 1, 2, \cdots, n)$;

(2) RBF kernel function is $\psi\left(x_k, x_l\right) = \exp\left(-\frac{\left\|x_k - x_l\right\|}{\sigma^2}\right)$; and

(3) sigmoid kernel function is $\psi\left(x_k, x_l\right) = \tanh\left(\varphi\left(x_k \cdot x_l\right) + \theta\right)$.

2.2 Limit displacement prediction model by LSSVM

The process of establishing a prediction model involves selecting training data and searching for regular internal data automatically. According to $FLAC^{3D}$ numerical simulation results, the displacement of deep roadway is caused by influencing factors such as depth *H*, bulk density *γ*, elastic ratio *E*, cohesion *c*, internal friction angle *φ*, Poisson ratio *μ*, and dilatancy angle *ψ*. Depth *H*, elastic ratio *E*, cohesion *c*, and internal friction angle *φ* were selected as training sample in this paper. According to the LSSVM principle, *α* and *b* are the solution for (4), and the RBF kernel function was chosen for the sequel. We solve function (2) by using the optimization toolbox of Matlab and compiling the corresponding LSSVM program. The optimization process for the limit displacement prediction model is shown in Fig. 1.

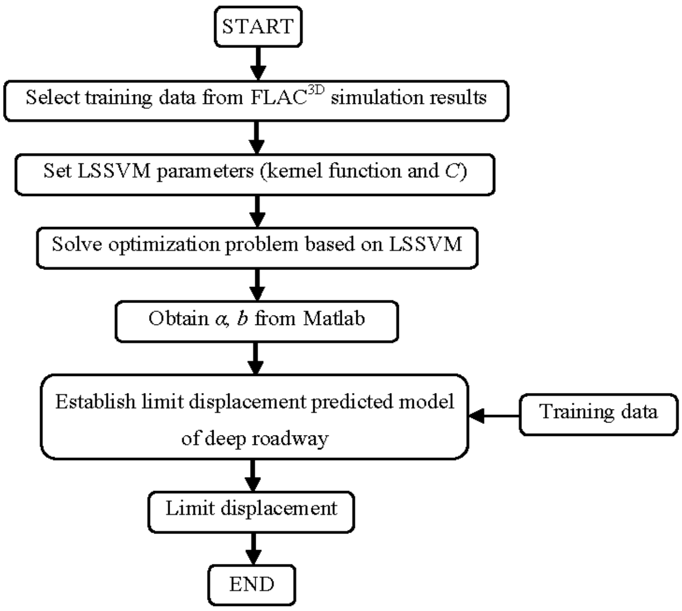

Fig. 1 Optimization process of limit displacement prediction of deep roadway.

3. Verifying the prediction model

Numerical simulation was established by $FLAC^{3D}$ using 64 sets of test samples, with each rock group consisting of 16 samples. In the limit displacement prediction model, 44 sets were randomly selected as training data, whereas the other 20 sets served as verifying data[24] (* marked in Table I).

Table 1 Data of Training Samples

No.	H/(m)	E/(GPa)	C/(MPa)	φ/(°)	U/(mm)	No.	H/(m)	E/(GPa)	C/(MPa)	φ/(°)	U/(mm)
1	400	2	0.34	28	21.13	33	800	2	0.34	28	53.3
2	400	1.2	0.2	26	31.57	34	800	1.2	0.2	26	74.46
3	400	0.8	0.15	24	41.59	35	800	0.8	0.15	24	97.72
4	400	0.5	0.1	22	54.48	36	800	0.5	0.1	22	123
5	450	2	0.34	28	22.19	37	850	2	0.34	28	57.62
6	450	1.2	0.2	26	33.18	38	850	1.2	0.2	26	80.55
7	450	0.8	0.15	24	43.99	39	850	0.8	0.15	24	105.66
8	450	0.5	0.1	22	58.11	40	850	0.5	0.1	22	133.45

9*	500	2	0.34	28	25.42	41*	900	2	0.34	28	62.58
10*	500	1.2	0.2	26	37.68	42*	900	1.2	0.2	26	87.63
11*	500	0.8	0.15	24	50.16	43*	900	0.8	0.15	24	114.96
12*	500	0.5	0.1	22	66.27	44*	900	0.5	0.1	22	145.9
13	550	2	0.34	28	30.21	45	950	2	0.34	28	67.68
14	550	1.2	0.2	26	44.15	46	950	1.2	0.2	26	94.89
15	550	0.8	0.15	24	58.78	47	950	0.8	0.15	24	124.49
16	550	0.5	0.1	22	77.1	48	950	0.5	0.1	22	158.63
17	600	2	0.34	28	35.65	49	1000	2	0.34	28	71.85
18	600	1.2	0.2	26	51.33	50	1000	1.2	0.2	26	100.8
19	600	0.8	0.15	24	68.18	51	1000	0.8	0.15	24	132.2
20	600	0.5	0.1	22	88.41	52	1000	0.5	0.1	22	168.8
21*	640	2	0.34	28	39.89	53	1050	2	0.34	28	75.57
22*	640	1.2	0.2	26	56.84	54	1050	1.2	0.2	26	105.37
23*	640	0.8	0.15	24	75.27	55	1050	0.8	0.15	24	137.63
24*	640	0.5	0.1	22	96.64	56	1050	0.5	0.1	22	175.34
25	700	2	0.34	28	45.47	57*	1100	2	0.34	28	79.53
26	700	1.2	0.2	26	64.02	58*	1100	1.2	0.2	26	109.57
27	700	0.8	0.15	24	84.39	59*	1100	0.8	0.15	24	142.14
28	700	0.5	0.1	22	106.97	60*	1100	0.5	0.1	22	180.28
29*	750	2	0.34	28	49.44	61	1200	2	0.34	28	84.99
30*	750	1.2	0.2	26	69.21	62	1200	1.2	0.2	26	118.02
31*	750	0.8	0.15	24	90.97	63	1200	0.8	0.15	24	153.95
32*	750	0.5	0.1	22	114.60	64	1200	0.5	0.1	22	196.24

According to a similar project experience, RBF kernel is selected for the sequel, $\gamma=\infty,\sigma^2=1$. A calculation is established for α and b, as shown in Table 2. A comparison of the LSSVM predicted value and the numerical simulation is shown in Table 3, which shows that the absolute error is within ±2mm (maximum is 5.1906mm) and the relative error is within ±2% (maximum is 5.2007%). The limit displacement prediction model was therefore reasonable and reliable.

Table2 Sample Data for the Prediction Model of Deep Roadway

No.	α	No.	α	No.	α	No.	α
1	54.00	12	14.48	23	5.37	34	7.83
2	-137.30	13	-37.59	24	-16.42	35	-22.44
3	312.90	14	57.42	25	28.83	36	38.04
4	-307.20	15	-25.24	26	-18.78	37	-25.17
5	33.00	16	-84.32	27	-20.02	38	-20.77
6	501.50	17	379.57	28	87.67	39	87.01
7	-828.60	18	-492.62	29	-93.30	40	-83.51
8	1112.00	19	485.91	30	6.61	41	-30.03
9	-1122.30	20	-421.50	31	63.45	42	114.26
10	396.00	21	123.88	32	-51.18	43	-74.79
11	-14.20	22	-0.74	33	7.92	44	9.47

Table 3 Comparison Analysis of LSSVM Prediction Value and Numerical Simulation

No.	Simulation value/(mm)	Prediction value/(mm)	Absolute error/(mm)	Relative error/(%)
1	25.42	24.4084	-1.0165	-3.9980
2	39.89	41.2229	1.3316	3.3381
3	49.44	51.4584	2.0184	4.0825
4	62.58	63.1176	0.5376	0.8591
5	79.53	77.6404	-1.8896	-2.3760
6	37.68	38.7302	1.0467	2.7776
7	56.84	54.9456	-1.8911	-3.3273
8	69.21	67.8148	-1.3916	-2.0108
9	87.63	86.4626	-1.1674	-1.3322
10	102.99	105.4213	2.4307	2.3601
11	50.16	52.7677	2.6086	5.2007
12	75.27	73.0078	-2.2643	-3.0082
13	90.97	86.5820	-4.3883	-4.8239
14	114.96	113.4013	-1.5587	-1.3559
15	142.14	146.6051	4.4671	3.1428
16	66.27	63.6660	-2.6001	-3.9237
17	96.64	98.9826	2.3473	2.4290
18	114.60	119.3170	4.7182	4.1171
19	145.90	147.7324	1.8324	1.2559
20	180.28	175.0915	-5.1906	-2.8792

4. Application Examples

4.1 Project summary

No. 9 Coal Mine of Hebi Coal Industry is a deep, high-stress soft rock roadway with a tunnel burial depth of -420m. While the shaft inset, waiting chamber, and bottom yard of the service shaft are being excavated, nonlinear mechanics arise and seriously influence normal mine sinking and drifting engineering. The central substation and pump chamber is the subsequent engineering, and the cross section of the chamber is large. Avoiding large deformation is difficult for a traditional U structure and bolt-shotcrete. Therefore, a new support scheme and construction technology should be studied.

4.2 Establishing numerical calculation model

The numerical model constructed by FLAC^{3D} is presented in Fig. 2. The length, width, and height of the model are 30m, 5m, and 30m, respectively. The model is meshed into 7576 elements. A straight wall and half-closed arch of the roadway (5 m × 4 m) is placed in the center of the model, and the heights of the arch and straight wall are 2.5 and 1.5 m, respectively. All sides of the model are fixed. The Moore–Coulomb criterion is used to numerically simulate the linear broken surface. The major principal stress of the model is 25.2 MPa, the minor principal stress 14.6 MPa, and the vertical stress is 21 MPa. The material mechanical properties of the model are shown in Table 4. The design parameters of the substation supporting scheme are as follows:

1) Rock-bolt: roof and side with resin bolt, Φ22mm@0.7m×0.7m, l=2.5m; base with steel pipe, Φ32mm@0.7m, l=2.5m;

2) anchor cable: steel strand, Φ18.9mm@1.4m×2.1m, l=8m;

3) mesh: round steel, Φ6@1.47m×0.91m; grid, 0.07m;

4) C20 shotcrete;

5) high convex strip: GDT30/140×20×2000.

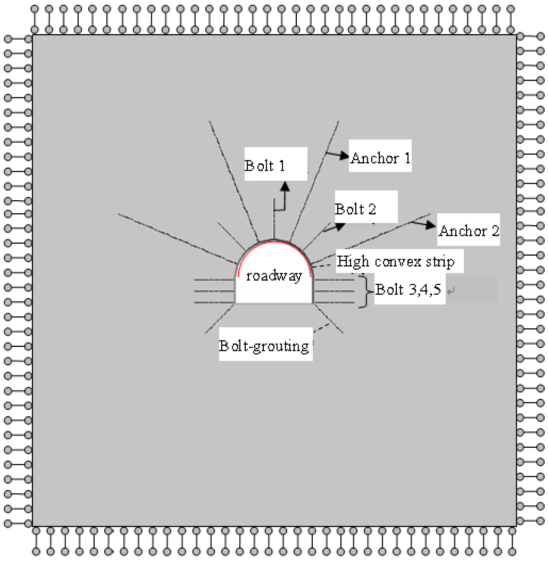

Figure 2. Numerical calculation model

Table 4 Mechanical Properties of Materials Used in the Numerical Model

	Young's modulus (GPa)	Poisson's ratio	Cohesion (MPa)	Internal friction Angle (°)	Density (kN/m^3)	Dilation angle (°)
Surrounding rock	1.3	0.35	0.2	27	22.5	10

The distribution characteristics of displacement by FLAC^{3D} are shown in Fig. 3. The limit displacement is 56.84 mm and is distributed in the chamber bottom.

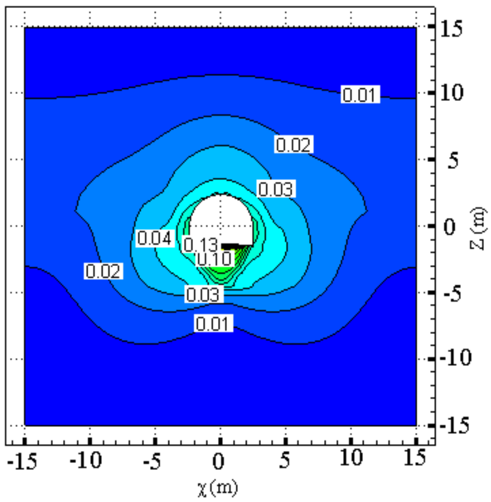

Fig. 3 Distribution of displacement by FLAC3D for deep roadway.

4.3 Analysis of results for limit displacement prediction

After studying the support effect for a substation, the limit displacement was determined to occur in the chamber bottom, and then the chamber roof. In this paper, the prediction of the limit displacement of a substation bottom using the LSSVM model is reported, and the displacement was determined to be 54.95mm. After two years of on-site deformation monitoring, the central substation convergent data tended to 58.6mm, 54.1mm, and 66.1mm values, the average of which is 59.6 mm. A comparison of the LSSVM prediction value and the $FLAC^{3D}$ numerical simulation is shown in Table V.

Table 5 Comparison of LSSVM Predicted Value and FLAC3D Numerical Simulation

	Numerical simulation by $FLAC^{3D}$/(mm)	On-site monitoring value/(mm)	Prediction value/(mm)	Absolute error/(mm)	Relative error/(%)
Limit displacement of substation	56.84		54.95	-1.89	-3.44
		59.6	54.95	4.65	8.46

The high convex strip and bolt–mesh–cable coupling support effectively control the large deformation and ensures the stability and safety of the deep roadway. Thus, the LSSVM prediction model has great accuracy and meets deep roadway engineering requirements.

5. Conclusions

1. This paper establishes a limit displacement prediction model by using LSSVM theory. The model works effectively and meets deep roadway engineering requirements.
2. The results have great significance in estimating the stability of a deep roadway in advance and provides important guidance in making reasonable construction decisions.

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