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Sensitivity analysis of the influencing factors of slope stability based on LS-SVM

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Abstract. This study proposes a sensitivity analysis method for slope stability based on the least squares support vector machine (LS-SVM) to examine the influencing factors of slope stability. The method uses LS-SVM as an algorithm for machine learning. An appropriate training dataset is established according to the slope characteristics, and a testing dataset is designed orthogonally. Results of the testing data in the experiment design are calculated after training using the LS-SVM model. The sensitivity of the slope stability of each factor is examined via gray correlation analysis. The results are consistent with those of the traditional Bishop analysis and can be used as a reference for optimizing slope design.

Keywords: slope stability; sensitivity analysis; orthogonal design; least squares support vector machine; gray correlation

1. Introduction

The stability of a slope affects human safety and property interests; thus, stability has practical significance in the study of slopes (De Vita *et al*. 2013, Sdao *et al*. 2013). The main methods for analyzing slope stability include the finite element method and the limit equilibrium method (Berisavljević *et al*. 2015, Eid and Rabie 2016, Farah *et al*. 2015, Gao *et al*. 2013, Ozbay and Cabalar 2014). Among the two approaches, the limit equilibrium method is the more common solution. It assumes that the material is a rigid body and considers the ratio of the anti-sliding force to the sliding force a safety factor. By contrast, the finite element method separates the differential equation and finds the solution with the variational principle or weighted margin. When the material is assumed to be elasto-plastic, applying strength reduction obtains the safety factor. The aforementioned methods are based on certain assumptions and equilibrium conditions in the established calculation model, and the safety factor is calculated. However, these methods typically provide varying safety factors for the same slope because of their different prerequisites. The traditional analysis methods for the sensitivity of a slope stability factor are essentially based on the computation of change parameters, such as intensive computational expenditure and the

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preparation of a large data set. With the development of artificial intelligence, machine learning algorithms, such as neural networks, the cloud computing model, and fuzzy reasoning, can be used to obtain the results of a testing set (Ge *et al*. 2013, Singh *et al.* 2012, Li *et al.* 2015). Machine learning algorithms provide a new approach for analyzing slope stability and have been applied to such task in varying degrees (Chen *et al.* 2011, Dehnavi *et al*. 2015, Mohamed *et al.* 2012). Neural networks are among the most widely used algorithms. However, they should be specified in advanced structures, and they tend to over-rely on the study sample. In particular, input space, which is a set of all possible input values, is high dimensional for practical problems. Sample data are only sparsely distributed in space to obtain high-quality training data. Huge amounts of data are required, but sample data are limited in most cases. Thus, many authors have proposed new algorithms to improve neural networks. The application of the aforementioned algorithms to the stability analysis of slopes has been conducted at different levels; among these algorithms, however, neural networks have been the most widely used. Support vector machines (SVMs) are among the most successful improvements to neural networks. For example, the least squares SVM (LS-SVM) can solve many disadvantages of neural networks. LS-SVM prevents neural networks from requiring a large training dataset for support. It is based on theory of minimum risk probability; hence, satisfactory prediction results can be obtained even with a small sample (Moraes *et al.* 2013, Qi *et al*. 2013, Zhang *et al*. 2014).

Slope stability is subject to a number of factors, including height, slope, internal friction angle, and cohesion. These factors present uncertainties, and thus, cannot be treated equally. Different factors of slope stability sensitivity should be considered. Eventually, we focus on the factor with the strongest impact on slope stability. If the main factors cannot be accurately identified during slope stability evaluation, then inaccurate results will be obtained and incorrect judgments will be made. Therefore, slope stability evaluation is necessary for analyzing the sensitivity of slope stability factors. Many authors have conducted studies on this topic (Yu *et al*. 2008, Chen *et al*. 2007, Myhra *et al*. 2014). With regard to the method for calculating the impact of the sensitivity of different factors, slope stability is influenced by the height, slope, internal friction angle, and cohesive force of the slope. The analysis of the sensitivity of different factors and the identification of the dominant factor can provide an important theoretical basis for preventing and controlling slope failure. ANOVA and regression analysis are two of the most commonly used methods to determine the relationship among different factors. These methods require the sample to fulfill the classical probability distribution (Chen *et al*. 2015, Garg *et al*. 2014, Moraes *et al.* 2013, Vatanpour *et al.* 2014). By contrast, the gray correlation distribution method is not limited by this requirement. Its advantages include its simple and highly accurate calculation (Liu and Hu 2013). In accordance with LS-SVM theory, the training LS-SVM model calculates the testing set of the orthogonal design. Gray correlation analysis (GCA) is then conducted to measure the sensitivity of different factors. The sensitivity analysis of the influencing factors of slope stability can then be realized.

2. Factor sensitivity analysis theory based on LS-SVM

LS-SVM, orthogonal design, and GCA are involved in factor sensitivity analysis. The proposed method, which is for the sensitivity analysis of the influencing factors of slope stability, uses LS-SVM as a machine learning algorithm and builds the testing set using the orthogonal design method. The influence degree of each factor is measured via GCA.

2.1 LS-SVM algorithm

The least square is regarded as an error function and can be directly solved using Eq. (1). The mathematical expression for the prediction problem is as follows

$$\begin{cases} \min\limits_{w.b.e} J\left(w,b,e\right)=\dfrac{1}{2}w^T w+\dfrac{\gamma}{2}\sum\limits_{i=1}^{n}e_i^2 \\ s.t. \quad y_i = w^T\varphi\left(x_i\right)+b+e_i, \quad i=1,\cdots,n \end{cases} \tag{1}$$

where w is the weight vector, γ is the regularization parameter, e_i is the error variance, $\varphi(\cdot)$ is the nonlinear mapping from input space to high-dimensional feature space, and b is the bias vector.

The Lagrange function of the optimization problem, i.e., Eq. (1), is as follows

$$L\left(w,b,e,\alpha\right)=J\left(w,b,e\right)-\sum_{i=1}^{n}\alpha_i\left\{w^T\varphi\left(x_i\right)+b+e_i-y_i\right\} \tag{2}$$

where α_i is the Lagrange multiplier and $\alpha_i \neq 0$.

From the corresponding Karush–Kuhn–Tucker conditions, the following equations can be established

$$\begin{cases} \dfrac{\partial L}{\partial w}=0 \\ \dfrac{\partial L}{\partial b}=0 \\ \dfrac{\partial L}{\partial e_i}=0 \\ \dfrac{\partial L}{\partial \alpha_i}=0 \end{cases} \Rightarrow \begin{array}{c} w=\sum\limits_{i=1}^{n}\alpha_i\varphi\left(x_i\right) \\ \sum\limits_{i=1}^{n}\alpha_i=0 \\ \alpha_i=\gamma e_i, \quad i=1,\cdots,n \\ w^T\varphi\left(x_i\right)+b+e_i-y_i=0, \; i=1,\cdots,n \end{array} \tag{3}$$

The equations on the right side of Eq. (3) are solved to obtain α and b. Thus, the output value of the new input vector can be calculated according to the following formula

$$K\left(x,x_i\right)=\varphi\left(x\right)^T\varphi\left(x_i\right), \tag{4}$$

where $K\left(x,x_i\right)=\varphi\left(x\right)^T\varphi\left(x_i\right)$ is the kernel function that maps two vectors onto a separable hyper-variable product space. The radial basis function (RBF) is one of the most popular kernel functions for SVM. RBF can be described as follows

$$K\left(x,x_i\right)=e^{-\frac{\left\|x_i-x\right\|^2}{2\sigma^2}}, \tag{5}$$

where σ^2 is the squared bandwidth, which is optimized through an external optimization technique during the training process.

2.2 Orthogonal design principle

Orthogonal design is a method for scientifically arranging and analyzing multifactor tests using an orthogonal table. This table is abbreviated as $L_n(m^k)$, where n is the test time, m is the factor level, and k is the number of the factors. The number of occurrences of a level in each column of the orthogonal table is equal, and all combinations of different levels of any two columns are shown. Thus, the experimental points are well-ordered and uniform in the interval, in addition to being typical. The orthogonal design can significantly reduce the number of experiments and help find the rule for a system. The basic steps of the test scheme design are as follows:

(1) A clear purpose for the orthogonal test is stated to clarify the objective of the experiment.
(2) The test factors are selected to determine the parameter level. The actual problem is studied comprehensively, and the main factors are chosen. The numbers of factors and levels are determined. An appropriate orthogonal table is selected.
(3) The experiment is conducted to obtain the results. The horizontal number in the table is changed to the corresponding horizontal number to obtain the experiment results of the orthogonal design.

2.3 GCA principle

GCA involves determining the influence degree of the factors on the research object by investigating their geometric proximity, analyzing their influence, and comparing their quantitative correlations to measure the correlation degree among them.

From the determined reference matrix $x_0(t)$ and comparison matrix $x_i(t)$ (i = 1, 2,..., n; t = 1, 2,..., m), the combined matrix X in the analysis of the correlation degree can be obtained via

$$X = \begin{bmatrix} x_0(1) & x_0(2) & \cdots & x_0(m) \\ x_1(1) & x_1(2) & \cdots & x_1(m) \\ \vdots & \vdots & \cdots & \vdots \\ x_n(1) & x_n(2) & \cdots & x_n(m) \end{bmatrix} \tag{6}$$

Matrix X becomes dimensionless, thereby resulting in

$$\hat{x}_i(t) = \frac{x_i(t) - \min\{x_i(t)\}}{\max\{x_i(t)\} - \min\{x_i(t)\}}. \tag{7}$$

The normalization process of matrix $\hat{X}$ is

$$\hat{X} = \begin{bmatrix} \hat{x}_0(1) & \hat{x}_0(2) & \cdots & \hat{x}_0(m) \\ \hat{x}_1(1) & \hat{x}_1(2) & \cdots & \hat{x}_1(m) \\ \vdots & \vdots & \cdots & \vdots \\ \hat{x}_n(1) & \hat{x}_n(2) & \cdots & \hat{x}_n(m) \end{bmatrix}. \tag{8}$$

The equations for solving the correlation coefficient are

$$\xi_i\left(k\right)=\frac{\Delta_{\min}+\lambda\Delta_{\max}}{\Delta_i\left(k\right)+\lambda\Delta_{\max}}\ , \tag{9}$$

$$\Delta_i\left(k\right)=\left|\hat{x}_0\left(k\right)-\hat{x}_i\left(k\right)\right|, \tag{10}$$

where 0 #*i* *n*, 1 #*k* *m*; $D_{\max}$ ($D_{\min}$) is the maximum (minimum) among all the absolute differences $D_i(k)$; and *l* is the resolution coefficient, which is generally *l* = 0.5.

The correlation coefficient matrix *R* can be obtained from Eq. (9) as follows

$$R=\begin{bmatrix} \xi_1(1) & \xi_1(2) & \cdots & \xi_1(m) \\ \xi_2(1) & \xi_2(2) & \cdots & \xi_2(m) \\ \vdots & \vdots & \cdots & \vdots \\ \xi_n(1) & \xi_n(2) & \cdots & \xi_n(m) \end{bmatrix} \tag{11}$$

The equation for the correlation degree is generally expressed as

$$r_i=\frac{1}{m}\sum_{k=1}^{m}\xi_i\left(k\right). \tag{12}$$

The correlation degree of each factor can be obtained using Eq. (12).

3. Sensitivity analysis process for the influencing factors of slope stability

The sensitivity analysis of the factors that influence slope stability is typically based on actual situations. The variation range of each factor was provided, and we gradually changed these factors following certain steps before calculating the corresponding change in the safety factor value. We obtained each factor for slope sensitivity by comparing the relatively basic index values. The influencing factors of slope stability include slope geometry and material mechanics parameters. These parameters typically consist of bulk density, internal friction angle, cohesion, slope angle, and slope height. The mode of slope failure generally varies, and common modes include circular sliding failure and wedge failure. The dataset on the right side is established as the training set based on different damage patterns and then used to train the LS-SVM model. The complete sensitivity analysis process can be divided into the following steps (Fig. 1).

(1) The possible mode of the slope failure to be analyzed is determined, and the dataset that is consistent with the slope failure mode is selected as the training set.
(2) LS-SVM is trained using the training set, and the predictable LS-SVM model is established.
(3) The factor number, change level, and orthogonal table design are determined according to the slope characteristics.
(4) The level number of the orthogonal table is changed into the corresponding concrete level value according to the change interval of the influencing factors, and then the prediction set is built.

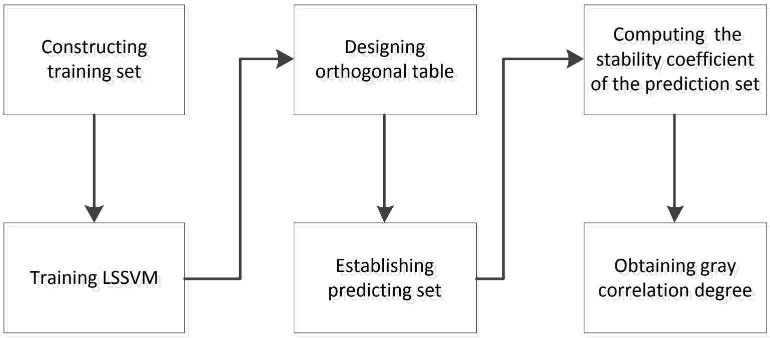

Fig. 1 Analysis process for factor sensitivity

(5) The LS-SVM model established in the second step is used to obtain the slope safety factor under each level number of the prediction set.
(6) The correlation degree of each factor is obtained through GCA, and then the influence degree of each sensitivity factor is determined.

4. Application example and effect analysis

4.1 Application example

The following influencing factors of a slope are considered: soil sample bulk density (γ) of 19.06 kN/m^3, cohesive force (c) of 11.71 kPa, internal friction angle (Φ) of 28°, slope angle (β) of 35°, slope height (H) of 21 m, and pore pressure coefficient (μ) of 0.11.

The failure mode of the slope is the circular arc mode with one planar sliding surface. We can construct the training dataset based on the collected dataset of the arc failure of the slope (Table 1) (Sakellariou and Ferentinou 2005). RBF, also called the Gaussian function, have wider applicability and easier parameter settings than other kernel functions. Hence, it is selected to implement LS-SVM. However, the performance of RBF is determined by a penalty factor (λ) and a kernel parameter (σ). The grid search algorithm is a popular method used to obtain the optimal solutions for λ and σ. Suppose λ and σ are initially limited within a certain range. The different values of the λ of N and the σ of M are used to form the λ and σ of N*M for training LS-SVM. The errors of the results are computed based on the λ and σ of N*M according to the training set. The λ and σ values that can obtain the minimum computational error are regarded as the optimal solutions. The penalty factor λ and the kernel parameter σ are determined to be 399.78 and 91.8933, respectively, using a grid search algorithm. The mapping relationship between the input and output variables is established using the LS-SVM model based on the training samples in Table 1. The slope safety factors can be predicted using the prediction model for the established LS-SVM.

In the present study, the factor number of the slope is 6 and the bit level of the identified factors is 5. The range of the influencing factors is [80%, 120%]. The orthogonal table $L_{25}(5^6)$ is selected and used to establish the prediction set (Table 2). After training, the LS-SVM model is used to calculate the safety factor of each sample across different factors (Table 2, last column).

Table 1 Training dataset used in the analysis

Sample no.	Input variable						Output variable
	γ (kN/m^3)	c (kPa)	Φ (°)	β (°)	H (m)	μ	SF
1	18.80	14.40	25.02	19.98	30.6	0	1.876
2	18.77	30.01	9.99	25.02	50	0.1	1.400
3	19.97	19.96	36	45	50	0.5	0.829
4	22.38	10.05	35.01	45	10	0.4	0.901
5	18.77	30.01	19.98	30	50	0.1	1.460
6	28.40	39.16	37.98	34.98	100	0	1.989
7	19.97	10.05	28.98	34.03	6	0.3	1.340
8	13.97	12.00	26.01	30	88	0	1.021
9	18.77	25.06	19.98	30	50	0.2	1.210
10	18.83	10.35	21.29	34.03	37	0.3	1.289
11	28.40	29.41	35.01	34.98	100	0	1.781
12	18.77	25.06	9.99	25.02	50	0.2	1.180
13	16.47	11.55	0	30	3.6	0	1.000
14	20.56	16.21	26.51	30	40	0	1.250
15	18.66	26.41	14.99	34.98	8.2	0	1.111
16	13.97	12.00	26.01	30	88	0.5	0.626
17	25.96	150.1	45	49.98	200	0	1.199
18	18.46	25.06	0	30	6	0	1.090
19	19.97	40.06	30.02	30	15	0.3	1.841
20	20.39	24.91	13.01	22	10.6	0.4	1.400
21	19.60	12.00	19.98	22	12.2	0.4	1.349
22	20.96	19.96	40.01	40.02	12	0	1.841
23	17.98	24.01	30.15	45	20	0.1	1.120
24	20.96	45.02	25.02	49.03	12	0.3	1.529
25	22.38	99.93	45	45	15	0.3	1.799
26	18.77	19.96	19.98	30	50	0.3	1.000
27	21.78	8.55	32	27.98	12.8	0.5	1.030
28	21.47	6.90	30.02	31.01	76.8	0.4	1.009
29	21.98	19.96	22.01	19.98	180	0.1	0.991
30	18.80	57.47	19.98	19.98	30.6	0	2.044
31	21.36	10.05	30.33	30	20	0	1.700
32	18.80	14.40	25.02	19.98	30.6	0.5	1.111
33	15.99	70.07	19.98	40.02	115	0	1.111
34	21.98	19.96	36	45	50	0	1.021
35	19.08	10.05	9.99	25.02	50	0.4	0.649
36	19.08	10.05	19.98	30	50	0.4	0.649
37	17.98	45.02	25.02	25.02	14	0.3	2.091

Table 1 Continued

Sample no.	Input variable						Output variable
	γ (kN/m^3)	c (kPa)	Φ (°)	β (°)	H (m)	μ	SF
38	24.96	120.0	45	53	120	0	1.301
39	20.39	33.46	10.98	16.01	45.8	0.2	1.280
40	17.98	4.95	30.02	19.98	8	0.3	2.049
41	18.97	30.01	35.01	34.98	11	0.2	2.000
42	21.98	19.96	22.01	19.98	180	0	1.120
43	20.96	30.01	35.01	40.02	12	0.4	1.490
44	20.96	34.96	27.99	40.02	12	0.5	1.430
45	18.46	12.00	0	30	6	0	0.781
46	19.97	40.06	40.01	40.02	10	0.2	2.310
47	19.97	19.96	36	45	50	0.3	0.961
48	18.77	19.96	9.99	25.02	50	0.3	0.970
49	18.83	24.76	21.29	29.2	37	0.5	1.070
50	19.03	11.70	27.99	34.98	21	0.1	1.090
51	22.38	10.05	35.01	30	10	0	2.000
52	18.80	15.31	30.02	25.02	10.6	0.4	1.631

Table 2 Testing dataset established using the orthogonal design method

Sample no.	Input variable						Output variable
	γ (kN/m^3)	c (kPa)	Φ (°)	β (°)	H (m)	μ	SF
1	15.25	11.71	25.20	38.50	21.00	0.10	0.10
2	22.87	11.71	33.60	28.00	25.20	0.12	0.12
3	15.25	9.37	22.40	28.00	16.80	0.09	0.09
4	17.15	14.05	33.60	42.00	21.00	0.09	0.09
5	15.25	12.88	33.60	35.00	23.10	0.13	0.13
6	20.97	11.71	28.00	35.00	18.90	0.09	0.09
7	22.87	12.88	28.00	42.00	16.80	0.10	0.10
8	20.97	9.37	25.20	42.00	25.20	0.13	0.13
9	17.15	11.71	30.80	31.50	16.80	0.13	0.13
10	19.06	14.05	25.20	35.00	16.80	0.12	0.12
11	19.06	11.71	22.40	42.00	23.10	0.11	0.11
12	15.25	14.05	28.00	31.50	25.20	0.11	0.11
13	20.97	14.05	30.80	28.00	23.10	0.10	0.10
14	22.87	14.05	22.40	38.50	18.90	0.13	0.13
15	22.87	10.54	25.20	31.50	23.10	0.09	0.09
16	20.97	10.54	33.60	38.50	16.80	0.11	0.11

Table 2 Continued

Sample no.	Input variable						Output variable
	γ (kN/m^3)	c (kPa)	Φ (°)	β (°)	H (m)	μ	SF
17	17.15	10.54	22.40	35.00	25.20	0.10	0.10
18	22.87	9.37	30.80	35.00	21.00	0.11	0.11
19	19.06	12.88	30.80	38.50	25.20	0.09	0.09
20	15.25	10.54	30.80	42.00	18.90	0.12	0.12
21	20.97	12.88	22.40	31.50	21.00	0.12	0.12
22	19.06	10.54	28.00	28.00	21.00	0.13	0.13
23	19.06	9.37	33.60	31.50	18.90	0.10	0.10
24	17.15	9.37	28.00	38.50	23.10	0.12	0.12
25	17.15	12.88	25.20	28.00	18.90	0.11	0.11

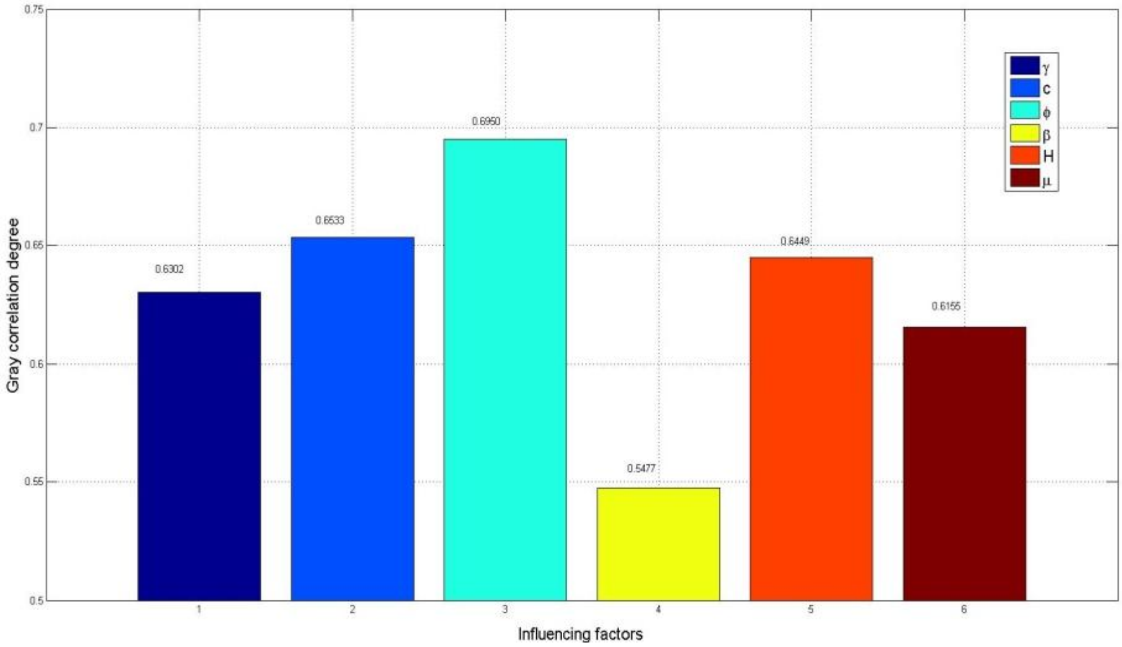

Fig. 2 Comparison of the correlation degree between each factor and stability

4.2 Effect analysis

The sensitivity of each factor can be determined based on Table 2 using GCA. The correlation degree between each factor and stability can be analyzed. The results are presented in Fig. 2.

Fig. 2 shows that the influences of friction angle and cohesive force are the most significant among the influencing factors. Slope height, bulk density, and pore pressure coefficient rank second, whereas slope angle exerts the least influence. Thus, we can identify various factors associated with the degree of stability using the proposed method. To test the validity of the

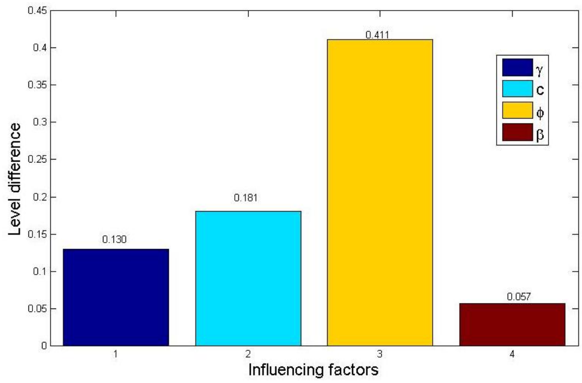

Fig. 3 Rank comparison of the four influencing factors and the safety factor

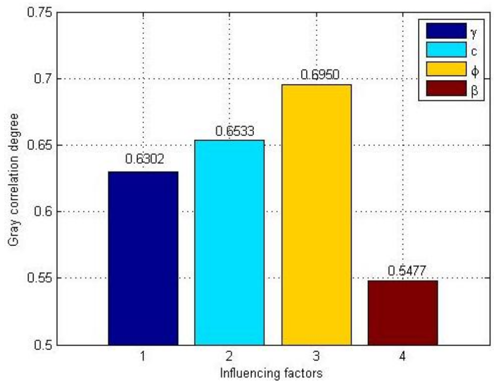

Fig. 4 Correlation degree comparison of the four influencing factors and the safety factor

proposed method, its calculation results are compared with those of traditional analysis methods. From engineering practice, four influencing factors of slope stability (i.e., internal friction angle, cohesion, slope angle, and bulk density) have been determined to exert considerable impact on the safety factor. Among traditional analysis methods, the simplified Bishop method is the most common. The influences of four factors, namely, internal friction angle, cohesion, slope angle, and bulk density, are considered in the analysis. The sensitivity of each factor is calculated using the simplified Bishop method. A single-factor change is adopted in the calculation process. The single factor ranges from 80% to 120%, whereas the other parameters remain unchanged. The safety factor can be calculated at each level. Then, we calculate the safety factor for each parameter. Subsequently, the Bishop method is used to calculate the safety factor. The difference level of each factor can be determined. The results are presented in Fig. 3.

The ranks presented in Fig. 3 reflect the influences of various factors on the stability of slope sensitivity. This figure shows that the internal friction angle exhibits the highest sensitivity. The sensitivity of cohesion is higher than that of bulk density, whereas slope angle demonstrates the least sensitivity. Fig. 4 shows the correlation degrees of the four factors from Fig. 2. This result is consistent with that of the analysis based on LS-SVM (Fig. 4). Therefore, the method used in this study is reasonable and reliable for the sensitivity analysis of slope stability. Limit equilibrium methods (e.g., the Bishop method, Swedish arc, and the Fellenius method) regard soil as a rigid body without considering its deformation. These methods are inconsistent with respect to actual soil property. Limit equilibrium methods obtain the main sliding surface with significant uncertainty and do not consider the effect of uneven stress distribution. By contrast, LS-SVM exhibits a strong nonlinear mapping capability. It can perform nonlinear mapping without knowing the relationship among data and the specific distribution of data. LS-SVM is more reasonable than the Bishop method or other limit equilibrium methods in analyzing the sensitivity of the slope safety factor (He *et al.* 2003).

5. Conclusions

The stability analysis of a slope is a complex scientific problem. On the basis of previous research, the LS-SVM model is used to study the sensitivity of the influencing factors of slope stability instead of previous neural network models and conventional limit equilibrium methods. The proposed approach can precisely predict the safety factor of a slope given a small dataset. The orthogonal design method is adopted to reduce the number of experiments, and GCA is used to measure the influence degree of each factor. The slope dataset of a circular sliding failure mode with one planar sliding surface is used for LS-SVM training. The application of the orthogonal design method obtains a factor test set within the change in interval influence, and the degree of each influencing factor is measured using GCA. We compare the analysis results with those of conventional analysis methods. The findings show that the proposed method can correctly obtain the sensitivity of the influencing factors in slope stability analysis, help distinguish between primary and secondary influencing factors, and provide a reliable reference for optimizing slope design. The proposed method does not require a huge amount of data and exhibits high efficiency. The sample is also not required to conform to the classical general distribution. The proposed method for the sensitivity analysis of slope safety factors exhibits significant advantages.

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