Comparisons of rock slope stability evaluations between extreme learning machine and genetic algorithm-support vector regression

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ABSTRACT

For practicing engineers, analyses of rock slope stability can be quite challenging because appropriate software for such problems are often not user-friendly. Analyzing rock slopes using simple theoretical solutions, such as Limit equilibrium method (LEM), is a difficult task, due to the complex features of a rocks mass including joints, faults, discontinuities and anisotropies. Therefore, this paper aims to develop convenient tools using a hybrid approach known as genetic algorithm-support vector regression (GASVR) that can provide a quick assessment of rock slope stability. GA-SVR searches for the optimal SVR parameters using genetic algorithms (GA), and then adopts those optimal parameters to construct the SVR model. The training data was acquired using the solutions from the finite element upper and lower bound limit analysis methods. In addition, the solutions from the artificial neural network (ANN) trained by extreme learning machine (ELM) will be adopted for comparisons purposes. ELM is a new ANN algorithm that uses the single-hidden layer feedforward (SLFNs) to randomly choose the hidden nodes and analytically determines the output weights of SLFNs. The results showed that using GA-SVR and ELM for prediction could provide prompt and highly accurate results. It would be helpful for practical designs.

Keywords: extreme learning machine; genetic algorithm; support vector regression

1. INTRODUCTION

Stability evaluation of rock slopes is a difficult problem often face by geotechnical engineers. Most rock masses generally contain joints, faults, isotropic and discontinuities problems. For practicing engineers, most of the commercial software are based on the limit equilibrium method and Mohr-Coulomb failure criterion. However, it is too simple and unsuitable to deal with rock slope problems associated with many uncertainties. This study adopts artificial intelligence techniques, genetic algorithm-support vector regression (GASVR) and extreme learning machine (ELM), to predict the stability numbers N_r, proposed by Li et al (2008).

The results are based on the finite element limit analysis methods (A.V. Lyamin et al. 2002a; 2002b and Krabbenhoft et al. 2005). It should be noted that N_r is based on the Hoek-Brown failure criterion, and thus the results obtained would be very different from those based on the Mohr-Coulomb failure criterion. In this study, limit analysis methods (LA) are used to study various types of the rock masses firstly. Then, GASVR and ELM are employed to predict the stability numbers, N_r, as shown in Equation (1).

$$N_r = \frac{\sigma_{ci}}{\gamma HF} \tag{1}$$

2. Evaluation process

The numerical limit analysis methods are adopted to perform rock slope stability analyses, and thus stability numbers are obtained. GASVR and ELM were used to complete training at the second stage. The results can assess rock slope stability by providing the factor of safety. The latest Hoek-Brown failure criteria, Hoek et al. (2002), is shown as below:

$$\sigma_1' = \sigma_3' + \sigma_{ci}\left(m_b \frac{\sigma_3'}{\sigma_{ci}} + s\right)^a \tag{2}$$

Where

$$m_b = m_i \exp\left(\frac{GSI - 100}{28 - 14D}\right) \tag{3}$$

$$s = \exp\left(\frac{GSI - 100}{9 - 3D}\right) \tag{4}$$

$$a = \frac{1}{2} + \frac{1}{6}\left(e^{-GSI/15} - e^{-20/3}\right) \tag{5}$$

m_b, s and α rely on the geological strength index (*GSI*), which represents the rock quality and the value is between 5 and 95. σ_{ci} and m_i represent the intact uniaxial compressive strength and material constant, respectively. The disturbance factor *D*, which ranges between 0 and 1, represents the degree of disturbance for rock mass.

As mentioned previously, a range of parameters are taken into account. By doing parametric studies, a large quantity of stability numbers can be provided. In this study, five parameters are chosen as the training inputs, slope angle (β), *GSI*, m_i, *D*, horizontal seismic coefficient (k_h). The target is to predict the stability numbers N_r, and thus the factor of safety can be obtained. Using the proposed GASVR and ELM techniques, the predicted models are automatically created.

3. METHODOLOGY

3.1 GASVR

Support vector regression (SVR) is a regression version of support vector machine (SVM) which has emerged as an alternative and powerful technique to solve regression problems by introducing an alternative loss function. The SVR formulation follows the principle of structural risk minimization, seeking to minimize an upper bound of the generalization error rather than minimize the prediction error on the training set. SVR generalization performance and efficiency depends on the regularization parameter (C), bandwidth of the kernel function (σ^2) and the tube size of ε-insensitive loss function (ε) being set correctly. However, no general guidelines are available to select these parameters (Gunn 1998; Cristianini and Shawe-Taylor 2000; Vapnik 1999). In general, when selecting SVR parameters, most researchers follow the trial and error procedure, first by building a few SVR models based on different parameter sets, then testing them on a validation set to obtain optimal parameters. However, this procedure can be very tedious and requires some luck. Different parameter settings can cause significant differences in performance.

In contrast to optimizing SVR parameters as mentioned above, this study uses GASVR, which optimizes all SVR parameters simultaneously. This model adopts GA to seek the optimal values of SVR parameters thereby improving the prediction accuracy. Fig. 1 illustrates the algorithm process of the GA-SVR model. Table 1 gives an overview of GA parameter settings used in this study.

Initial populations comprising of chromosomes were randomly generated from GA to search for the optimal values of SVR parameters. The values of the three parameters, I.e., regularization parameter (C), bandwidth of the kernel function (σ^2), and the tube size of insensitive loss function (ε), were directly coded in the chromosomes with real value data.

Table 1. GA parameter settings

Number of generations	100
Population size	10
Selection type	Roulette wheel
Crossover type	Simulated binary
Mutation type	Inverse nutation
Crossover probability	0.85
Mutation probability	0.04

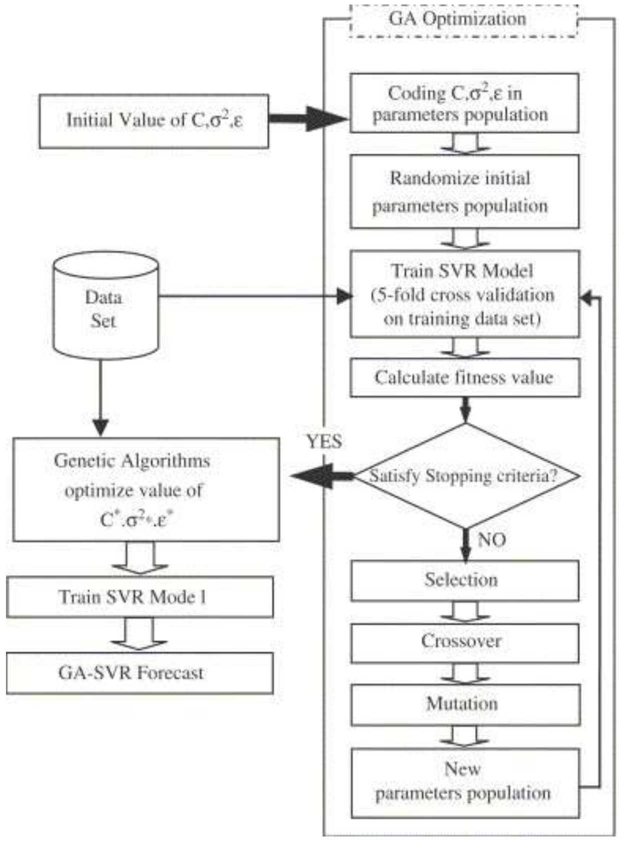

Fig. 1. GA-SVR model

3.2 ELM

ELM is a single hidden layer feed-forward neural networks (SLFNs) proposed in Huang et al. (Huang, Zhu, and Siew 2004) which randomly selected the input weights and analytically determines the output weights of SLFNs. Obviously, the computational burden of ELM learning is significantly less than that of the classical feedforward neural network (FFN) training (Demuth et al. 2014). In theory, this algorithm tends to provide the best generalization performance at an extremely fast learning speed. The ELM algorithm can be easily implemented, tends to reach the smallest training error, obtains the smallest norm of weights and the good generalization performance, as well as running extremely fast (Huang et al. 2006).

ELM has several interesting and significant features different from traditional popular gradient-based learning algorithms for feed forward neural networks:

These include

- The learning speed of ELM is extremely fast. The learning phase of ELM can be computed in seconds or less for many applications.
- For feed-forward neural networks the ELM algorithm looks much simpler compared to most other learning algorithms.
- ELM has a better generalization performance than other gradient-based learning such as back propagation in most cases.

4. CASE STUDY

A few case studies were conducted to ascertain the validity of the proposed techniques for stability evaluation of rock slope stability. In this study, comparisons are made between the stability numbers obtained from limit analysis and those obtained from GASVR and ELM. Table 2 shows comparisons of factors of safety obtained from ELM and GASVR to those obtained from LA with k_h=0 and D=0.7. Whereas Table 3 shows comparisons of factors of safety obtained from ELM and GASVR to those obtained from LA with k_h=0 and D=1. It should be noted that LA results are obtained by observing the original stability charts, and thus the errors would be significant.

Table 2. Comparison of factors of safety: LA, ELM and GASVR with k_h=0 and D=0.7

Slope parameters				LA	ELM	GASVR
H(m)	β(°)	*GSI*	m_i			
41	50	46	25	2.36	2.19	2.29
41	55	49	25	1.99	1.84	2.21
46	55	50	25	1.91	1.74	1.81
57	49	48	25	2.12	1.86	1.79
58	50	55	25	4.91	4.40	4.70
60	48	54	25	5.33	4.51	4.40
60	52	56	25	4.35	3.95	4.02
38	39	57	7	5.24	3.63	3.94
200	65	76	19	49.61	38.38	36.54
157	48	65	7	5.43	4.54	5.04
60	53	65	7	10.29	9.35	8.90
110	48	40	7	1.75	1.44	1.68

Finally, Table 4 shows comparisons of stability numbers obtained from ELM and GASVR to those obtained from LA with k_h=0.1 and D=1. In fact, the results of ELM and GASVR are fairly similar which is the same as previous findings. In addition, the factor of safety for k_h=0.1 is smaller than that for k_h=0. This trend is reasonable.

Table 3. Comparison of factors of safety: LA, ELM and GASVR with k_h=0 and D=1

Slope parameters				LA	ELM	GASVR
H(m)	B(°)	GSI	mi			
41	50	46	25	1.30	1.27	1.23
41	55	49	25	1.05	1.13	1.08
46	55	50	25	1.02	1.08	1.00
57	49	48	25	1.14	1.09	1.18
58	50	55	25	3.13	2.80	3.20
60	48	54	25	3.00	2.80	2.70
60	52	56	25	2.71	2.57	2.65
38	39	57	7	2.51	2.34	2.40
200	65	76	19	35.62	30.68	36.62
157	48	65	7	3.74	3.26	3.54
60	53	65	7	6.45	6.81	7.00
110	48	40	7	0.80	0.78	0.86

Table 4. Comparison of factors of safety: LA, ELM and GASVR with k_h=0.1 and D=1

Slope parameters				LA	ELM	GASVR
H(m)	β(°)	*GSI*	m_i			
41	50	46	25	0.92	0.89	0.84
41	55	49	25	0.81	0.78	0.73
46	55	50	25	0.78	0.74	0.80
57	49	48	25	0.80	0.76	0.72

5. CONCLUSIONS

For most of cases, the stability numbers are bracketed within ±10% based on the numerical upper bound and lower bound limit analysis methods. The results can be presented as chart solutions. However, there are too many stability charts, which would be too complicated for engineers to apply when evaluating rock slope stability.

To improve or reduce manual reading errors during the use of stability charts, two methods GASVR and ELM are used to train rock slope stability prediction models. R^2 (the coefficient of determination) is used to estimate the performance of both GASVR and ELM. Results from both studies show that the R^2 values are close to 95%, which means the models have great generalization performances and provide highly accurate results. The time for creating both the GASVR and ELM models is less than 3 minutes; this is a more time-efficient approach when compared to conventional slope stability assessments, particularly when dealing with lots of slopes stability estimations simultaneously. Results of this study suggest that GASVR and ELM are typically reliable prediction tools for the evaluation of rock slope stability. However, it should be indicated that the presented technique is only suitable for preliminary evaluations. Detailed investigations are still required when the slope is critical.

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