Analysis of Meizoseismal Area's Highway Rock and Slope Geology Using Decision Tree Evaluation Model

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ABSTRACT: *Based on the highway rock of meizoseismal areas, we selected the slope of Guanggan expressway fault zone as our research object and did a kinetic stability evaluation as well as an anti-seismic optimal measurement research on the slope. After analyzing the geological environment conditions of the research area, this study discussed about the genetic mechanism and developmental distribution characteristics of the geologic hazards of rocky slope. With the combination of decision tree evaluation model, this study established a systematic hazard evaluation system of highway rock and slope geology.*

Keywords: Rumerical modeling, Minging of liberation layer, Mine pressure behavior rule, Environmental management technology

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1. Introduction

Decision tree algorithm was a concept learning system (CLS) put forward by Hunt, et al. [1] in 1960's. Until the end of 1970's, J·Ross Quinlan used information gain of information theory in the construction of decision tree's nodes to put forward ID3 algorithm and improved it to C4.5 algorithm in 1990's [3]. Besides the algorithm that based on information theory, decision tree also includes algorithms that are based on minimum Gini index, like CART [4], SLIQ [5] and SPRINT, etc. [6]. In the form of tree structure which is similar to flow chart, decision tree can be used to express knowledge and rules and its model mainly consists of nodes and branches. Generally, each decision tree has one root node and the root node has no father node, while every other node has only one father node. Every node can have its own child node which is called internal node. The numbers of child nodes are determined by the forms of models. A node that has no child node is called leaf node. Internal node represents the test on a property, which is corresponding to a property used to partition data set as well as the judgement rules of the property. Leaf nodes are corresponding to classes that partition data set and different leaf nodes can be corresponding to the same class. The rule of classification can be established through the path from root node to leaf nodes and different paths are corresponding to different rules, thus classification forecasting of data can be decided according to the model of decision tree [7-9].

The slope earthquake response refers to the slope response caused by earthquake, including accelerated speed, speed, displacement and internal force, etc. caused in slope [10]. Main research methods used in slope kinetic stability at present are quasi-static method, Newmark sliding block analysis, model testing method and numerical analysis method, etc. It is generally recognized that the influence of earthquake load on slope stability is mainly because the inertia force of earthquake causes the increase of sliding force of slope, which lowers safety factors. Slope's failure mode, distribution and scale are determined by earthquake power and slope's geometrical and physical characteristics [11]. Based on the geological model research and geological process analysis, this study used the method that combined qualitative analysis and quantitative evaluation as well as used the knowledge of engineering geology, rock mechanics and earthquake mechanics to do a comprehensive research. On the basis of field research and laboratory experiment as well as using the numerical modeling method to consider different heights and different excavation angles of slope, this study analyzed the static force and kinetic stability of slope in fault zone.

2. Characteristic of Slope In Fault Zone

This study took Guanggan expressway fault zone slope as the research object, which mainly located in G4 section and had fragile rock and poor slope stability due to the effect of back mountain fault [12-13].

2.1 Slope Characteristics of One Section of Highway

Slope of K13+090-168 section of Guanggan expressway was a typical slope in fault zone. It was 35 m high and 78 m long, angled for 25° and excavated with three levels. Its lithology was phyllite with thin stratified structure and rock mass was in broken and loose structure. Underground water was undeveloped and no underground water was shown upon slope. Because of the fault, fracture developed and rock was soft. The quality level of rock mass was □.

The slope was designed as three-level slope, and main anti-slide measurement was slide-resistant pile combined with framework anchor cable. The first level was slide-resistant pile and the second and third level were pressure grouting with anchored frame and diamond-type lattice grassing. Excavation slope magnitude was 1:1. The slide-resistant pile was 20 m long, 10 m high and sectional dimension was 2*3 m. The secondary platform was arranged with 14 slide-resistant piles. During the detailed investigation, the construction of slope was finished and slope was overall stable with the support of piles. Some parts might have soil slide due to the rainfall and the unstable part was the edge of slope's left side, which was mainly the loose soil slide with rainfall.

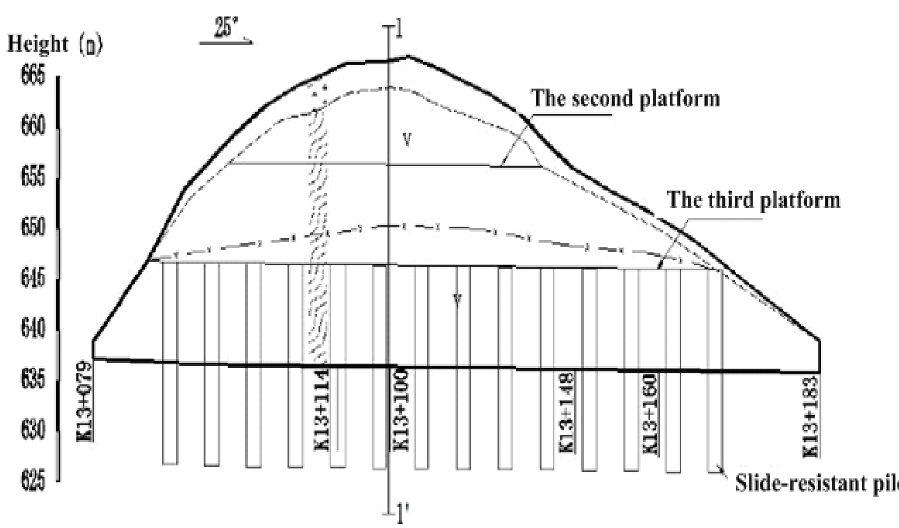

Figure 1. Elevation of the slope in K13+090-168 section of fault zone

The slope was already damaged that slide-resistant piles were slanted, frames and anchor heads were damaged and slope collapsed. Field investigation showed that all slide-resistant piles moved forth or slanted, especially the slide-resistant piles in the middle of the slope, which deformed obviously. Slope collapse and frame beam damage happened on the second platform. The back of slope showed obvious tension crack which was about 2-5 cm wide and 60 cm deep. The slope had poor stability like it showed in figure 1.

2.2 Kinetic Parameter Experiment of Rock Mass of Slope in Fault Zone

This research studied kinetic parameter of rock mass of four slopes in G4 section in fault zone and combined with the rock mass characteristics of the slope in this study to obtain the comprehensive parameter value. Due to the frangibility of the rock in fault zone's slope, it was difficult to have dynamic triaxial test indoors. Thus, this study mainly used supersonic field test to accomplish rock kinetic parameter experiment. FDP204SW ultrasonic tester and the matched compressional and shear wave transducer were used to have rock acoustic wave test, which consisted of launching system and receiving system. This study mainly tested the rate of decay and joints developed degree of 15-35 cm of excavated slope surface by chiseling two ends manually, testing longitudinal wave velocity and transverse wave velocity of rock and detailedly describe testing parts.

Acoustic wave test is the electrical pulse transport from transmitter to piezoelectric materials made transducer to stimulate the wafer of transducer to produce acoustic wave and launch to rock mass. Acoustic waves were spread in the form of elastic waves and received by transducer. Transducer Transformed acoustic energies into electrical signals and sent them to the receiver. After being magnified, their waveforms were displayed in the oscillograph tube screen of receiver, as it showed in figure 2.

Figure 2. Main parts of acoustic waves monitor

Parameter calculation mainly includes calculation of longitudinal wave velocity and transverse wave velocity as well as relevant dynamical elasticity parameter calculation [14-15]. The calculation formulas of longitudinal wave velocity and transverse wave velocity were as follows:

$$V_P = \frac{L}{t_P - t_0} \tag{1}$$

$$V_S = \frac{L}{t_S - t_0} \tag{2}$$

Dynamical elasticity parameter calculation formula was:

$$E_d = \rho V_P^2 \frac{(1+\mu)(1-2\mu)}{1-\mu} \times 10^{-3} \tag{3}$$

$$E_d = 2\rho V_S^2 (1+\mu) \times 10^{-3} \tag{4}$$

$$\mu = \frac{\left(\frac{V_P}{V_s}\right)^2 - 2}{2\left[\left(\frac{V_P}{V_S}\right)^2 - 1\right]} \tag{5}$$

$$G_d = \rho V_S^2 \times 10^{-3} \quad (6)$$

$$K_d = \rho\left[\left(3V_P^2 - 4V_S^2\right)/3\right]\times 10^{-3} \quad (7)$$

V_P was longitudinal wave velocity (m/d) and V_S was transverse wave velocity (m/s); L was the distance between transmitter and the central point of transducer (m), which was accurate to 0.001 m; t_P was the travel time of longitudinal wave in test piece (s) and was accurate to 0.1 μs; t_S was the travel time of transverse wave in test piece (s) and was accurate to 0.1 μs; t_0 was the zero propagation of instrumentation system (s); E_d was dynamic modulus of elasticity (MPa); ρ was the density of test piece (g/cm3); μ was poisson ratio; G_d was dynamic shear modulus of soils (MPa); K_d was dynamic bulk modulus (MPa). Calculation results have been shown in table 1.

Slope location	Measuring point position	Longitudinal wave velocity V_P (m/s)	shear wave velocity V_S (m/s)	Soil natural density ρ_0 (g/cm3)	Poisson ratio μ	Dynamic modulus of elasticity E_d (GPa)
K13+090-168 changing slope section	Distance to left side of slope 63m; 2.5m high	1780	900	2.5754	0.33	5.54
	Distance from right side of second-level slope to sideline 15 m; 3 m high	3240	1532		0.36	16.39
	Left side of the first-level slope phyllite	3300	1584		0.35	17.45
	Distance from right side of second-level slope to sideline 10 m; 3 m high	2020	1000		0.34	6.89
	Distance to left side of slope 5 m	1330	670		0.33	3.08
	Sideline of left side of slope 20 m	1850	906		0.34	5.68
	boulder	3300	1460		0.29	21.48
	boulder	3288	1800		0.39	14.39

Table 1. Calculation results of slope kinetic parameter of G4 fault zone

3. Construction of Evaluation Model of Rock Slope Geologic Hazards

This study did an evaluation research on the rock slope geologic hazards along the highway from 10 properties, which were slope aspect, slope height, natural grade, slope shape, rock structure, lithological association, characteristics of structure stability, relationship with causative fault, the distance from causative fault and excavation angle. The evaluation of rock slope geologic hazards was highly nonlinear and was related to many influence factors, thus this study used C4.5 decision tree algorithm to construct evaluation model of rock slope geologic hazards along the highway as well as based on Bagging and Adaboost algorithm to construct compositive decision tree model. All investigation samples in this study were divided randomly into two parts and the two parts had 140 sets of data and 300 sets of data respectively. The part with 140 sets of data was used as training samples while the other part with 300 sets of data was used as evaluating samples.

3.1 C4.5 Decision Tree Evaluation Model

The study took 140 sets of data randomly as training samples and used C4.5 algorithm to have decision tree model training. In the meantime, the confidence factor was set as 0.25 and the minimum sample size of leaf node was 2. After training the 140 sets of data, the obtained decision tree model had been shown in figure 3.

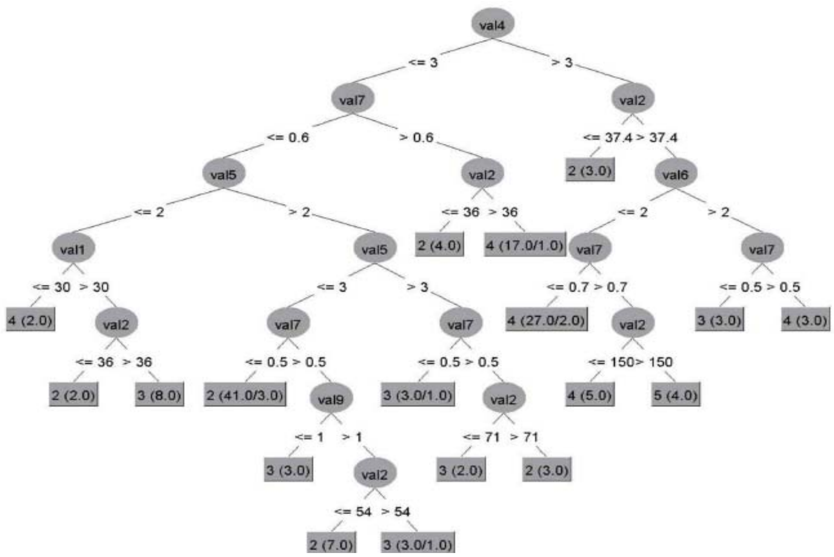

Figure 3. Sketch map of C4.5 algorithm decision tree model

3.2 Compositive Decision Tree Evaluation Model Based on Bagging

	Scale of tree	Numbers of leaf nodes
T1	29	15
T2	35	18
T3	31	16
T4	39	20
T5	27	14
T6	33	17
T7	29	15
T8	25	13
T9	29	15
T10	37	19
T11	31	16
T12	37	19
T13	29	15
T14	33	18
T15	28	14

Table 2 Basic parameters of Bagging based compositive decision tree model

In the process of using Bagging integrated algorithm to construct compositive decision tree evaluation model based on C4.5 algorithm, iterations were set as n, and through n times of iterations, n subtree models would be produced in compositive decision tree evaluation model. The form of each subtree model was similar to the decision tree model in upper segment. In evaluating and analyzing the rock slope geologic hazards, n subtree models' evaluation results should be calculated respectively, and according to the principles of voting, the evaluation with the most votes was selected as the final evaluation result of compositive decision tree model. Theoratically, more iterations means higher accurate rate of classified evaluations and better effect. However, it's not true in practical application. Due to training samples, too many iterations would result in reducing the accurate rate of compositive decision tree evaluation. After multiple times of attempts, this study decided to use 15 times of iterations in constructing rock slope geologic hazards evaluation model using Bagging algorithm. Basic parameters of subtree in Bagging and training samples based evaluation model have been shown in table 2.

3.3 Compositive Decision Tree Evaluation Model Based on Adaboost

In the process of using Adaboost integrated algorithm to construct compositive decision tree evaluation model based on C4.5 algorithm, iterations were set as n and through n iterations, n subtree models that were similar to the decision tree model in upper segment would be produced in compositive decision tree evaluation model. A relevant weight coefficient was determined in corresponding to each subtree model. After multiple times of attempts, this study decided to use 25 times of iterations in constructing rock slope geologic hazards evaluation model using Adaboost algorithm. When evaluating and analyzing the rock slope geologic hazards, 25 subtree model evaluation results should be calculated respectively, and the final evaluation result was determined with the combination of weight coefficient of each subtree model. Basic parameters of subtree in Adaboost and training samples based evaluation model have been shown in table 3.

	Scale of tree	Leaf nodes	Weight coefficient		Scale of tree	Leaf nodes	Weight coefficient
T1	31	16	2.27	T14	25	13	2.21
T2	27	14	2.61	T15	29	15	2.50
T3	22	12	1.75	T16	23	12	1.92
T4	29	15	2.29	T17	25	13	2.22
T5	19	10	2.01	T18	27	14	1.87
T6	32	17	2.46	T19	23	12	1.87
T7	25	13	1.70	T20	27	14	1.89
T8	25	13	2.37	T21	29	15	2.40
T9	26	13	1.98	T22	31	16	2.16
T10	27	14	1.93	T23	17	9	2.02
T11	1	11	2.21	T24	29	15	2.25
T12	33	17	2.28	T25	17	9	1.71
T13	24	13	2.15				

Table 3. Basic parameters of Adaboost based compositive decision tree model

3.4 Analysis of Evaluation Results

Accurate rate was the most direct parameter index of representing the evaluation results of evaluation models. It reflected the accuracy of classification forecasting of evaluation model to samples. Models that constructed with three different methods all could effectively evaluate rock slope geologic hazards, and after integrating C4.5 decision tree model using Bagging and Adaboost, the accurate rate of model evaluation increased. Compared with Bagging integrated algorithm, the accurate rate of Adaboost based compositive decision tree model basically achieved over 85%, which had better effect on evaluating samples.

Kappa statistics could be used to judge the classification results of classifier and the diversity factor of random assortment.

Computational formula was as follow:

$$Kappa = \frac{P_A - P_e}{1 - P_e} \tag{8}$$

P_A was the consistency ratio of classifier while P_e was the consistency ratio of random assortment. Kappa=1 means the decision of classifier was completely different with random assortment; Kappa=0 means classifier had the same decision with random assortment; Kappa=-1 means classifier had poorer decision than random assortment. The decision tree model based on Adaboost had the best Kappa statistic index among three models, which means it had the biggest difference between decision and random assortment, thus had the best classification effect.

Mean absolute error was the mean value of n times experiment's absolute error that used for judging diversity factor between predicted value and actual value. Absolute error was the absolute value of difference value between predicted value and actual value. Obviously, smaller value means better effect. Computational formula was as follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left| f_i - y_i \right| = \frac{1}{n}\sum_{i=1}^{n}\left| e_i \right| \tag{9}$$

f_i was the predicted value of classifier, y_i was actual value and e_i was the difference between predicted value and actual value. Compositive decision tree model that based on Adaboost had the smallest mean absolute error index in every experiment, which means it had the best evaluation effect among three models. However, Bagging based compositive decision tree model had bigger mean absolute error index than C4.5 based decision tree model, which means after using Bagging algorithm to integrate decision tree, although accurate rate increased to some extend, its difference between wrong evaluation result and actual value increased. Therefore, Adaboost based decision tree model had better evaluation effect in evaluating rock slope geologic hazards and had higher practical application value.

4. Conclusion

After investigating the engineering geology of Guanggan highway fault zone slope, we found that the slope structure of G4 section was simple and the slope mainly consisted of moderately strong and seriously weathered phyllite as well as quaternary system loose accumulation. Rock of G4 section slope was broken and joint fissures were developed. Rock structure was mainly broken, some parts were mosaic texture and loose structure and groundwater was weak. The level of rock quality was 4 to 5. G4 section slope had poor stability and local buckling phenomenon was severe. Main failure modes were wedge shape slide, surface accumulation and rock collapse, rock chipped off. Based on the decision tree theory, evaluation model of meizoseismal area highway rock slope geologic hazards is constructed, and compositive decision tree evaluation model that based on decision evaluation model was also constructed using Bagging and Adaboost algorithm. With the combination of research area examples, this study analyzes the evaluation effects of different models. The results indicates that decision tree evaluation model that based on evaluation theory has good effect in evaluating meizoseismal area rock slope geologic hazards and with further optimizing, the accurate rate can be raised, thus the evaluation method of meizoseismal area rock slope geologic hazards is further improved.

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