

Risk Assessment of Rockfall Hazards in a Tunnel Portal Section Based on Normal Cloud Model

Xin-tong Wang, Shu-cai Li, Xiu-yuan Ma, Yi-guo Xue*, Jie Hu, Zhi-qiang Li

Geotechnical and Structural Engineering Research Center, Shandong University,
Jinan 250061, Shandong, China

Received: 5 October 2016

Accepted: 11 January 2017

Abstract

In mountainous regions, rockfall is a typical geological disaster which might bring immense casualties and economic losses, but also endanger the safety of civil engineering construction. Many tunnels are being built in the southwest of China, thus a comprehensive assessment for rockfall risk is needed. For this purpose, in this paper, based on normal cloud model theory, we created a multi-index evaluation model for the rockfall risk assessment. Then, according to previous research and specific geological conditions, potential tunnel dangers are classified into four ranks, and some geological factors are considered as the principal factors. In order to fully express the opinions of experts, the qualitative indices were quantified by continuous value scale. Moreover, the value of each index is determined by expert scoring. In view of different evaluation units, we used the normalization method to make geological indices dimensionless. And three numerical characteristics (Ex , En , and He) were calculated by the cloud generator algorithm with MATLAB. In this study, we assigned the weight of indices by simple dependent function to avoid the influence of subjective. Finally, by means of a normal cloud generator, we determined the integrated certainty grades. To ensure the accuracy of the normal cloud model method, it was tested in rockfall cases in Jiefangcun tunnel. And the results obtained by the cloud model method are in good agreement with the practical situation. Moreover, the results are better than those of the AHP-FUZZY and artificial neural networks methods after comparison. The cloud model-based method realizes a multi-criteria assessment of the rockfall risk in tunnel portal section and provides a practical guide on safe tunnel construction for similar projects.

Keywords: rockfall, normal cloud model, risk assessment, tunnel entrance

Introduction

In recent years, increasing casualties and economic losses as a result of unexpected extreme environmental conditions have been noticed [1, 2], and rockfall is one of

the most serious geological hazards in mountain valleys, tunnels, and highways [3, 4]. Rockfall is a common type of rapidly moving landslide that greatly endangers the safety of tunnel construction [5-7]. In southwestern China, many tunnels have been built under limited geological conditions. Moreover, rockfall is the most common cause of landslide catastrophes in mountain areas of Sichuan Province [8]. Therefore, it is crucial to predict the

*e-mail: xygxieagle@163.com

occurrence probability of rockfall to ensure the safety of tunnel construction and normal operation of railways in southwestern China.

For trouble in quantifying the vulnerability, the lack of collected data, and the nature of rocks in a specific site [9-10], a lot of research has been carried out regarding rockfall risk in recent years. Specifically, in view of the influencing factors of rockfall hazards varying by project, a large number of outdoor experiments for rockfall have been carried out to test the main factors, for example the effects of rockfall volume [11], the size and shape of rockfall, fall paths, and trajectories [12-14]. Additionally, some other research has also assessed the risk of rockfall by using terrestrial lasers [1], GIS^{3D} software [5], and remote sensing spatial-temporal analysis [3].

In the past few decades, related studies have been carried out in various fields, such as mines, highways, road rock cut slopes, and scenic spots [3, 5, 9, 10, 15], proposing a great deal of methods and methodologies, for instance the analytic hierarchy process (AHP), the neural network (NN), the fuzzy mathematics theory (FMT), and so on [16-19]. And an overview of qualitative rockfall hazard assessment used in underground rock engineering was provided [20].

However, only several methods have been applied to assess the risk of rockfall in the slope of tunnels and highways. According to Russell, the Rockfall Hazard Rating System (RHRS) was created by adding geological and climatic factors [21]. Wang [22] found a quantitative rockfall risk assessment (QRA) applied to a slope and adopted a first-order second moment (FOSM) for an explicit assessment of uncertainty. Based on extensive field studies and the lumped-mass method, the stability assessment of the rockfall has been presented in Gökğöl tunnel by means of numerical analyses [23]. Ye [24]

provided a new evaluation method for the hazard grading of the rockfall at the slope segment of the tunnel entrance. Gao [17] raised an intelligence method for rockfall risk assessment based on a rough set and neural network to reduce the complexity and improve accuracy.

But the above-mentioned methods have their limitations. Most studies assign the weight of indices failing to avoid the influence of subjective and ignoring geotechnical uncertainty. Moreover, most studies cannot take multi factors into account. They evaluate the risk of rockfall by combining consequences and probability of the rockfall collapsing, but do not consider the reliability of evaluation results. Hence, there is a need to propose a multi-index comprehensively evaluation system in tunnels to assess the risk of rockfall by using normal cloud model theory.

Study Area

Chenglan railway is located in China's Sichuan and Gansu provinces, which has 33 newly constructed tunnels. The total length of all tunnels in this railway is 472.819 km, and there are 13 tunnels whose length is more than 10 km. Moreover, the geological conditions are extremely complex, and a great number of disasters, such as landslides, earthquakes and flooding, often occur during tunnel construction.

The Jiefangcun tunnel is situated in Songpan county, about 200 km north of Chengdu, the capital of Sichuan Province (Fig. 1). The Jiefangcun tunnel is 3.8 km long, making it one of the longest railway tunnels between Chengdu and Lanzhou. The buried depth of the tunnel ranges from 52 m to 601 m. The main geological formations crossed by the tunnel are limestone, sandstone, phyllite,

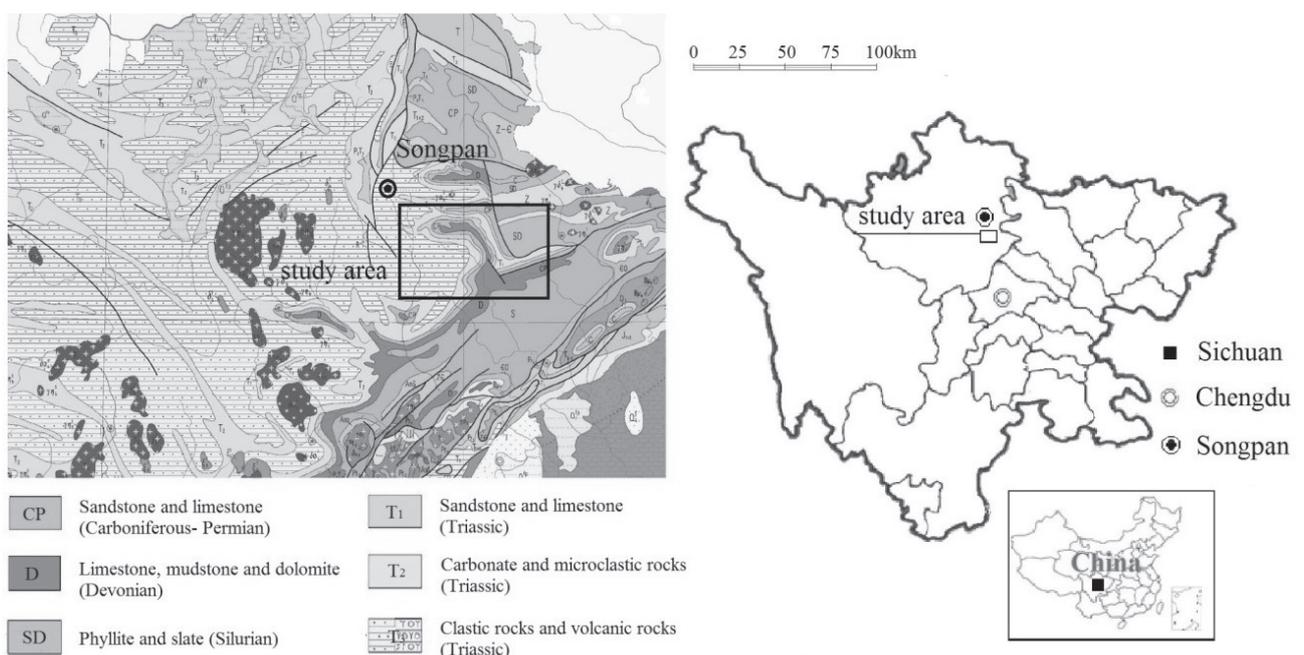


Fig. 1. Study area and geological condition of Songpan, Sichuan.

and mudstone. The study area lies within the eastern edge of the Tibetan Plateau, where terrain is incised intensely, and hills near the study area range from 2,370 m to 3,026 m in elevation. Moreover, intense erosion and weathering processes along the mountains have created a cliffy topography where the gradient ranges from 30° to 85°. In addition, the toe of high-steep slope above the tunnel portal section is encircled by National Highway No. G213. In order to ensure the safety of tunnel construction and reduce casualties and economic losses, the normal cloud model method has been applied to Jiefangcun tunnel. A brief risk assessment of rockfall hazards in the tunnel portal section is included in this paper.

Methodology

The concepts of rockfall hazard have various uncertainties, such as randomness and fuzziness. For example, the time rock will slide or fall and spatial distribution of rockfall are random, and the fuzzy bounds of affecting factors of rockfall hazard are difficult to be precisely defined. Thus, it is essential to introduce the cloud model to discuss the randomness and fuzziness of rockfall hazard. Cloud model theory was proposed in 1995 by Professor Li based on the study of probability and fuzzy sets theory [25-27]. Probability theory used normal distribution as an approximation to deal with random uncertainty, and the fuzzy sets theory uses normal membership function to reveal many fuzzy concepts. Cloud models can describe the inherent relationship between randomness and fuzziness and implement transformation between qualitative concept and quantitative characteristics. At present, cloud models have been researched in-depth and successfully applied to a lot of fields, for example simulation, evaluation, geological forecast, image processing, and other areas [28-30].

The Basic Definition of Cloud Model

The cloud model is a new graphic model that pictures the randomness and fuzziness of a concept to make it more concise and clear through comprehensive analysis [31]. Some quantitative numbers are adopted to represent qualitative concepts, and the cloud generator makes the uncertainly conversion between numbers and concepts much easier, as a powerful means of the cloud model.

Specifically, the definition is that X is the universe of discourse and Y is a qualitative concept connected with X . If the quantitative number x belongs to X and x is a random instantiation of concept Y , the certainty grade $\mu(x)$ for x belonging to Y is a random variable with a stable trend. The parameter $\mu(x)$ can be estimated as:

$$\mu: X \rightarrow [0,1] \quad \forall x \in X \rightarrow \mu(x) \quad (1)$$

The distribution of x is defined as cloud and each x is called cloud drop. The cloud drop is a tool as a quantitative

meaning to describe a qualitative concept. Moreover, the production process of cloud drops represents the uncertainty of conversion between qualitative concept and quantitative values. And the fuzziness and randomness of concepts are reflected in the certainty grade of cloud drops. Undoubtedly, cloud theory provides a feasible method that could build a connection between qualitative concepts and quantitative numbers.

Studies have shown that the normal cloud model is the most universal cloud model and a large number of random phenomena meet the normal distribution approximately [23]. If there is a number $x \in X$ is a random realization of the concept Y and satisfies $x \sim N(Ex, En^2)$ and $En' \sim N(En, He^2)$, the certainty grade of x belonging to concept Y satisfies:

$$\mu(x) = e^{-\frac{(x-Ex)^2}{2(En')^2}} \quad (2)$$

Then the distribution of x on universal set X is called the normal cloud, and each x is defined as a normal cloud drop.

Cloud Generator, Numerical Characteristics and Algorithm

Three numerical characteristics are essential to the cloud model: Ex , En , and He [32, 33], wherein Ex is the expectancy of cloud drop which is the best characterization of a qualitative concept. En is the entropy, depicting the randomness and fuzziness in the concept and also reflecting the granularity scale in the distribution. Hyper-entropy, He , the entropy of En , is used to measure the uncertainty of the membership degree and reflect the degree of dispersion of the cloud droplets. In addition, He describes the relationship between fuzziness and randomness clearly and controls the aggregation of a cloud drop.

By means of the cloud generator, cloud models make it possible to achieve bi-directional transformations between the intension and extension of a qualitative concept. The cloud transformations consist of the normal cloud generator(NCG) and the backward cloud generator(BCG). Moreover, the NCG realizes the transformation from the qualitative concept to the quantitative characteristic; in contrast, the BCG implements the transformation from the quantitative characteristic to the qualitative concept. The cloud transformations make it much easier for simulation of the human cognition process by computer. As many cloud drops as we require can be produced if the three quantitative characteristics are obtained.

The normal cloud generator algorithm can be displayed in algorithm as follows [34]:

- a) Calculate expectation En and the standard deviation He ;
- b) Generate a normally random number En' with expectation En and standard deviation $H: En' \sim N(En, He^2)$;
- c) x_i is a quantitative value of the qualitative concept, generate a normally random number x_i with expectation Ex and standard deviation En' : $x_i \sim N(Ex, En'^2)$;

d) Calculate certainty degree of quantitative values:

$$\mu(x_i) = e^{-\frac{(x_i - E_{ij})^2}{2(E_{ij}')^2}}$$

- e) Generate a cloud drop with the certainty degree $\mu(x_i)$ and the normally random number x_i ;
 f) Repeat steps (a) to (e) until n required cloud drops are generated.

Risk Assessment of Rockfall Hazards

The process of risk assessment of rockfall hazards based on the normal cloud model is shown in Fig. 2. Firstly, the geological information is collected, then the assessment index system and levels could be determined. Second, the three characteristics are calculated and cloud drops are built in a graphic way by the normal cloud generator with MATLAB software. Third, a simple dependent function is used to assign the weight. Then, according to the measured date and weight, the certainty grade of each level and the comprehensive certainty grade are obtained by the normal cloud generator, and the risk level of rockfall can finally be determined.

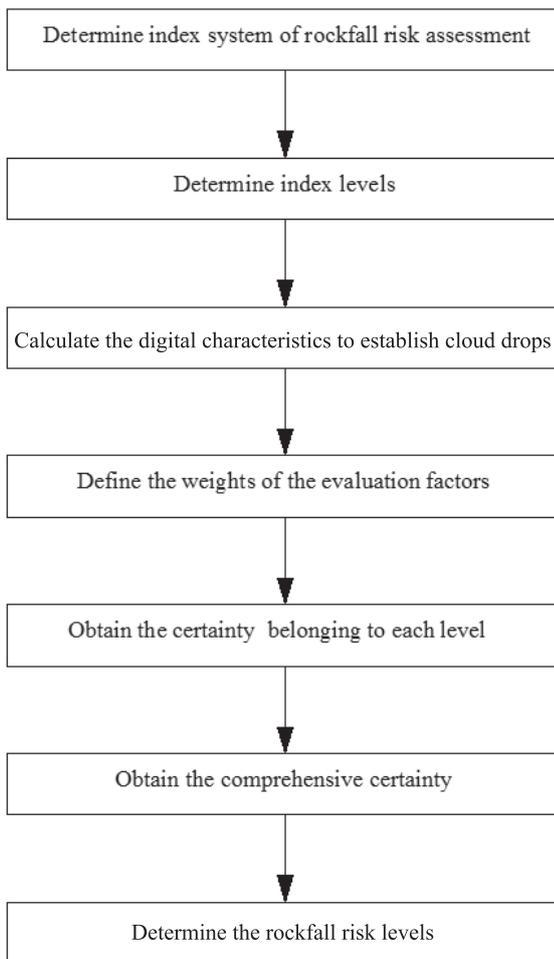


Fig. 2. The process of rockfall risk assessment based on normal cloud model.

Assessment Index System

Influencing factors of rockfall in a tunnel portal section is extremely complex, consisting of engineering factors and geological factors. Engineering factors are mainly used in dynamic risk assessment. Therefore, only geological factors are considered in this paper as engineering factors are unnecessary for rockfall risk assessment in static evaluation. Geological factors can be divided into geological conditions and hydrogeological conditions. Considering all the geological factors, the main factors include the following 10 indices belonging to three aspects: the characteristics of rockfall, slope condition, and natural environment (Fig. 3).

Assessment Index Levels

At present, rockfall hazards lack detailed risk assessment in a tunnel. In this paper, according to the results of previous studies [24, 35] and geological conditions of specific project, risk assessment levels of rockfall are divided into four levels: extraordinary stability (I), stability (II), less stability (III), and instability (IV) (Table 1).

Assessment indices should be quantified or corrected after assessment index levels are determined. According to the expert grading method, the qualitative geological indices are quantified by continuous value scale. Specifically, continuous value scale can fully express the opinions of experts compared with discrete value scale. The value of each index was determined by expert scoring (Table 2).

In rockfall shape, rounded and oblate-shaped blocks travel longer distances than others down the slope, followed by square-shaped blocks. Therefore, we adopted the idea that (0~25) represents oblate or rounded rocks, (26~50) represents bulk rocks, (51~75) represents column rocks, and (76~100) represents schistose or tapered rocks.

In rockfall shock types, (0~30) represent the rocks are slide and collapse; (31~50) represent the rocks are slide and roll; (51~70) represent the rocks collide with each other and bounce; (71~100) represent the rocks are fall and tumble.

In slope shape, (0~25) represents linear slope and the height is below 0.1 m, (26~50) represents convex slope and the height is 0.1-0.3 m, (51~75) represents concave slope and the height is 0.1-0.3 m, and (76~100) represents slopes with convex top and concave bottom with height above 0.3 m.

In slope lithology, (0~25) represents very hard rockfall with integrated structure, (26~50) represents hard rockfall with integrated structure, (51~75) represents fractured rockfall with non-integral structure, and (76~100) represents very fractured rockfall with non-integral structure.

In vegetational cover, (0~60) represents exposed bedrock or excavation surface is hardened; (60~80) represents fewer slope deposits consisting of some rock block, and less vegetation that is mainly grass; (80~90)

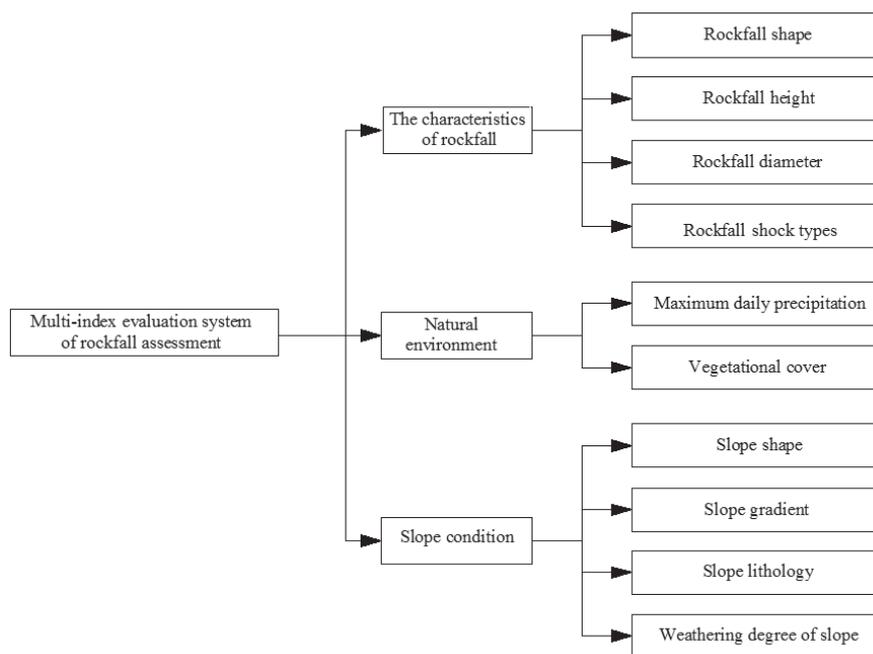


Fig. 3. Multi-index evaluation system of rockfall assessment in a tunnel portal section consisting of geological factors.

represents slope deposit thickness less than 1.0 m, and vegetation consisting of many shrubs and few trees; and (90~100) represents thick slope deposits, with vegetation consisting of many shrubs and many trees.

In view of the different evaluation units, the normalization method is used to make indices dimensionless, turning specific values of standard levels into account proportion. After normalization, the variation

tendency of the primitive value is maintained. The result means that the smaller the value, the lower the risk; it is normalized using Eq.(3). This formula should be calculated as [36]:

$$C'_i = \frac{C_i - C_{i\min}}{C_{i\max} - C_{i\min}} \tag{3}$$

Table 1. Rockfall risk assessment level parameter.

Assessment index	I	II	III	IV
Rockfall shape	Oblate	Blocky	Columnar	Schistose or tapered
Rockfall shock types	Slide and collapse	Slide and roll	Collide and bounce	Fall and tumble
Rockfall height (m)	0~20	20~50	50~100	>100
Slope gradient (°)	0~35	35~50	50~75	>75
Slope shape	Linear, slope height is below 0.1 m	Convex, slope height is 0.1-0.3 m.	Concave, slope height is 0.1-0.3 m.	Convex top and concave bottom slope height is above 0.3 m
Slope lithology	Very hard rockfall with integrated structure	Hard rockfall with integrated structure	Fractured rockfall with non-integral structure	Very fractured rockfall with non-integral structure
Weathering degree of slope	<5%	5%~15%	15%~30%	>30%
Rockfall diameter (m)	<0.3	0.3~1.0	1.0~3.0	>3.0
Maximum daily precipitation (mm)	0~25	25~75	75~250	>250
Vegetation cover	Exposed bedrock, or excavation surface is hardened	Fewer slope deposits consisting of some rock block, and less vegetation that is mainly grass	Slope deposit thickness is less than 1.0 m, and vegetation consists of many shrubs and few trees	Thick slope deposits, and vegetation consists of many shrubs and trees

Table 2. Normalized standard of rock fall risk assessment level parameter classifications.

Assessment index	I	II	III	IV
Rockfall shape	0~0.25	0.25~0.5	0.5~0.75	0.75~1
Rockfall shock types	0~0.3	0.3~0.5	0.5~0.75	0.75~1
Rockfall height (m)	0~0.1	0.1~0.25	0.25~0.5	0.5~1
Slope gradient (°)	0~0.35	0.35~0.5	0.5~0.75	0.75~1
Slope shape	0~0.25	0.25~0.5	0.5~0.75	0.75~1
Slope lithology	0~0.25	0.25~0.5	0.5~0.75	0.75~1
Weathering degree of slope	0~0.1	0.1~0.3	0.3~0.6	0.6~1
Rockfall Diameter (m)	0~0.075	0.075~0.25	0.25~0.75	0.75~1
Maximum daily precipitation (mm)	0~0.067	0.067~0.25	0.25~0.83	0.83~1
Vegetation cover	0~0.6	0.6~0.8	0.8~0.9	0.9~1

Conversely, the result means that the larger the value, the higher the risk; it is normalized using Eq.(4).

$$c'_i = \frac{c_{i\max} - c_i}{c_{i\max} - c_{i\min}} \tag{4}$$

In the formulas, c'_i is quantitative standard value of assessment index i . $c_{i\max}$ and $c_{i\min}$ are the maximum and minimum quantitative standard value of assessment index i .

Assessment Numerical Characteristics

Each variable has a boundary: $[B_{i\min}, B_{i\max}]$, and numerical characteristics can be expressed as [37]:

$$Ex_i = \frac{B_{i\max} + B_{i\min}}{2} \tag{5}$$

$$En_i = \begin{cases} \frac{Ex_2 - Ex_1}{3}, & i = 1 \\ \frac{Ex_{i+1} - Ex_i}{3}, & i \geq 2 \end{cases} \tag{6}$$

$$He = k \tag{7}$$

If a variable has only a single boundary such as $[-\infty, B_{i\min}]$ or $[B_{i\max}, +\infty]$, its default boundary parameter and Ex_i can be determined by the value of the upper and lower bounds. Then cloud parameters would be calculated by Eq.(3). He , which is the last digital characteristic of the cloud model, can be set as an appropriate constant k ($k < 0.5$), and its value is 0.01 in this paper.

Assessment Index Weight

In fact, the weight of each index is not absolute, but relative. And the weight should vary with specific data.

Therefore, we introduced a simple dependent function [38, 39] to determine the weight of indices in this paper. The simple dependent function is derived from the extension theory; furthermore, the relevancy between geological factors and rockfall risk can be determined quantitatively by dependent function. And the concept of distance in real variable function is extended to the concept of distance as the basis for the transformation between qualitative concept and quantitative characteristics.

Let c_i be the i index for the risk of rockfall hazards, N_j be the j level of risk assessment, v_i be specific data values for each index, and $V_{ij} = (a_{ij}, b_{ij})$ be the numerical range of the index c_i for level N_j . Then r_{ij} is the “distance” of the date v_i from the range V_{ij} . The main calculation steps for simple dependent function are as follows:

$$r_{ij} = \begin{cases} \frac{2(v_i - a_{ij})}{b_{ij} - a_{ij}}, & v_i \leq \frac{a_{ij} + b_{ij}}{2} \\ \frac{2(b_{ij} - v_i)}{b_{ij} - a_{ij}}, & v_i \geq \frac{a_{ij} + b_{ij}}{2} \end{cases} \tag{8}$$

In the formula, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$. Then:

$$r_{ij\max}(v_i, V_{ij\max}) = \max_j \{r_{ij}(v_i, V_{ij})\} \tag{9}$$

The larger level that index c_i belongs to, the greater the weight it should be given. The weight of index c_i for level N_j can be expressed as:

$$r_i = \begin{cases} j_{\max} \times (1 + r_{ij\max}(v_i, V_{ij\max})), & r_{ij\max}(v_i, V_{ij\max}) \geq -0.5 \\ j_{\max} \times 0.5, & r_{ij\max}(v_i, V_{ij\max}) < -0.5 \end{cases} \tag{10}$$

In contrast, this formula should be expressed as:

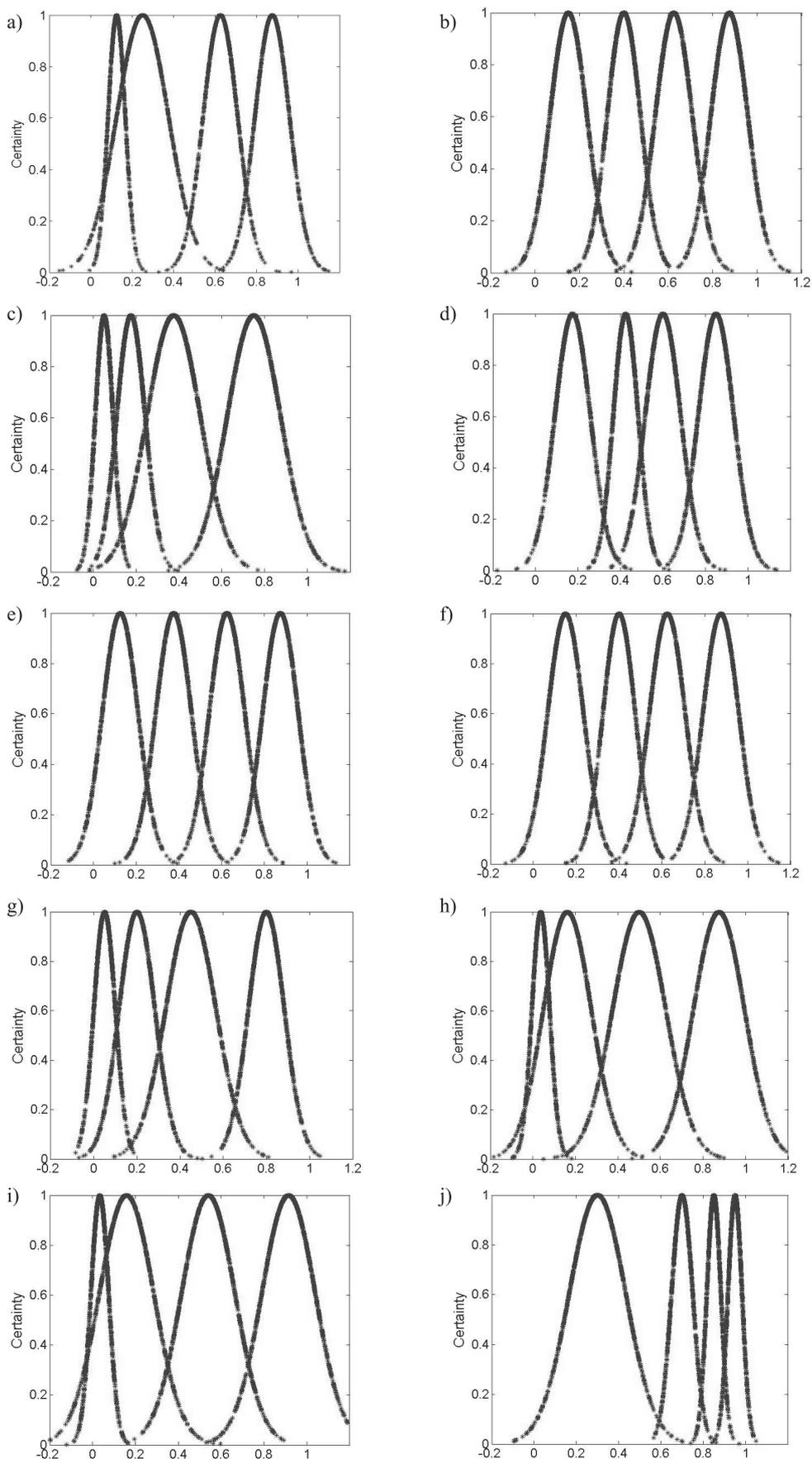


Fig. 4. Cloud for each evaluation factor established by the normal cloud generator. a) Rockfall shape, b) Rockfall shock types, c) Rockfall height, d) Slope gradient, e) Slope shape, f) Slope lithology, g) Weathering degree of slope, h) Rockfall diameter, i) Maximum daily precipitation, j) Vegetation cover.

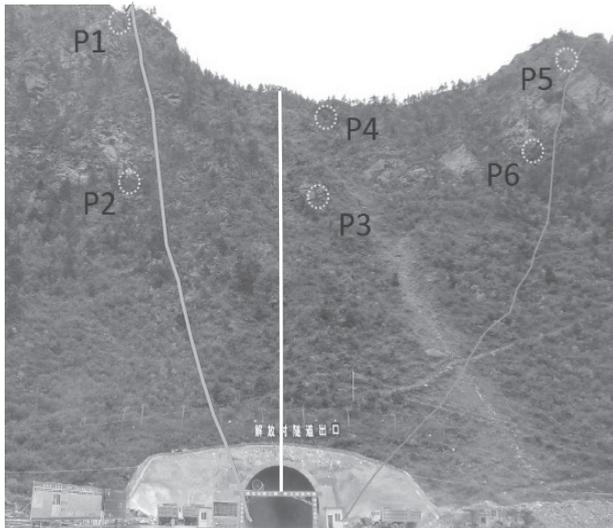


Fig. 5. The main region of dangerous rocks that remain prone to cause disasters above the Jiefangcun Tunnel entrance.

$$r_i = \begin{cases} (m - j_{\max} + 1) \times (1 + r_{ij_{\max}}(v_i, V_{ij_{\max}})), & r_{ij_{\max}}(v_i, V_{ij_{\max}}) \geq -0.5 \\ (m - j_{\max} + 1) \times 0.5, & r_{ij_{\max}}(v_i, V_{ij_{\max}}) < -0.5 \end{cases} \quad (11)$$

The weight of index c_i is:

$$a_i = \frac{r_i}{\sum_{i=1}^n r_i} \quad (12)$$

Generation of Normal Cloud Model

The normal cloud model of rockfall in a tunnel portal section can be set up using the normal cloud generator (Fig. 4). The certainty grade of each level of rockfall risk assessment in a tunnel portal section is calculated by the normal cloud generator. Then, combining with the simple dependent function, the integrated certainty degree M can be calculated as follows:

$$M = \sum_{i=1}^j \mu a_i \quad (13)$$

In the formula, μ is the certainty grade of an assessment level and a_i is the weight of index i .

Results and Discussion

We chose the Jiefangcun tunnel portal section as the study area. The main region and index parameter of dangerous rocks above the tunnel entrance is shown in Fig. 5, Table 3, and Table 5.

Based on the cloud model method, the process can be carried out as follows:

- 1) Based on the normalization method, the rockfall index parameters are normalized by using Eq.(3) or Eq.(4), and the computed values are shown in Tables 4 and 5.
- 2) In view of the simple dependent function, the weight of indices of rocks are taken as 0.331, 0.475, 0.426, 0.464, 0.338, 0.509, 0.678, 0.582, 0.306, and 0.509, respectively.

$$a = \begin{bmatrix} & P_1 & P_2 & P_3 & P_4 & P_5 & P_6 \\ a_1 & 0.078 & 0.031 & 0.079 & 0.022 & 0.054 & 0.067 \\ a_2 & 0.104 & 0.062 & 0.105 & 0.060 & 0.054 & 0.090 \\ a_3 & 0.070 & 0.064 & 0.084 & 0.048 & 0.083 & 0.077 \\ a_4 & 0.076 & 0.067 & 0.089 & 0.079 & 0.105 & 0.048 \\ a_5 & 0.023 & 0.058 & 0.042 & 0.068 & 0.066 & 0.081 \\ a_6 & 0.078 & 0.092 & 0.079 & 0.089 & 0.081 & 0.090 \\ a_7 & 0.104 & 0.123 & 0.105 & 0.119 & 0.108 & 0.119 \\ a_8 & 0.054 & 0.108 & 0.032 & 0.140 & 0.108 & 0.140 \\ a_9 & 0.047 & 0.055 & 0.047 & 0.054 & 0.049 & 0.054 \\ a_{10} & 0.078 & 0.092 & 0.079 & 0.089 & 0.081 & 0.090 \end{bmatrix} \quad (14)$$

$$K(a_1) = [0.331 \quad 0.475 \quad 0.426 \quad 0.464 \quad 0.338 \quad 0.509 \quad 0.678 \quad 0.582 \quad 0.306 \quad 0.509] \quad (15)$$

Table 3. Dangerous rock index parameters above the tunnel entrance.

Assessment index	p_1	p_2	p_3	p_4	p_5	p_6
Rockfall shape	Cuboid	Flat or cone	Square	Flat or cone	Plate	Cuboid
Rockfall shock types	Bounce, fall	Slide, roll	Collide with each other	Slide, roll	Slide, roll	Collide and bounce
Rockfall height	60 m	57 m	82 m	50 m	96 m	43 m
Slope shape	Convex top and concave bottom, slope height is 0.35 m	Convex, slope height is 0.2 m	Concave, slope height is 0.3 m	Concave, slope height is 0.2 m	Convex top and concave bottom, slope height is 0.4 m	Concave, slope height is 0.24 m
Slope gradient	58°	48°	45°	45°	55°	40°
Rockfall Diameter	0.3	0.5	0.1	0.6	0.5	0.6

Table 4. Normalized results of dangerous rock index parameters above the tunnel entrance.

Assessment index	p_1	p_2	p_3	p_4	p_5	p_6
Rockfall shape	0.50	0.15	0.65	0.15	0.30	0.55
Rockfall shock types	0.70	0.30	0.70	0.30	0.30	0.50
Rockfall height	0.30	0.25	0.41	0.28	0.48	0.21
Slope shape	0.75	0.46	0.68	0.46	0.80	0.60
Slope gradient	0.64	0.53	0.50	0.50	0.61	0.44
Rockfall diameter	0.70	0.50	0.90	0.90	0.50	0.40

Table 5. Normalized results of index parameter of the tunnel entrance.

Assessment index	Tunnel entrance	Normalized value
Slope lithology	Crushed rock with non-integral structure	0.50
Weathering degree of slope	Moderate degree	0.50
Maximum daily precipitation	120 mm	0.37
Vegetation cover	Vegetation consists of some shrubs and few trees	0.83

- 3) Based on the obtained normal cloud model method and the weight of indices, the numerical characteristics and the certainty grades can be discerned by the normal cloud generator by using Eq.(13).
- 4) The evaluation results of rocks are presented in Table 6.

The results of the proposed cloud model-based method were compared with that of AHP-FUZZY [18, 40] and Artificial Neural Networks (ANN) methods [19, 41-42]. In the AHP-FUZZY model, the weight was assigned by the Analytic Hierarchy Process method, and the priorities of each index were determined according to experts' opinions. Fuzzy theory was introduced to address the imprecise index system. Then a comprehensive evaluation vector was established by performing the fuzzy operation between the set of fuzzy weights and the fuzzy relationship matrix. On the other hand, in the ANN model an artificial neural network was established with three layers. The input and output layers represent independent variables and dependent variables of the system, respectively. Moreover, the hidden layer is used to perform the transformations. Specifically, the input layer has 10 neurons and the output layer has four neurons in this study. Furthermore, ANN is used for estimating outputs about the levels of assessment by using the inputs of rockfall shape, slope gradient, rockfall diameter and other seven factors. In short, the calculated results of the

normal cloud model method, AHP-FUZZY, and ANN are listed in Table 6.

In Table 6, each rock can be generally classified within four status levels from low to high. Considering the overall results of the cloud model method, the levels of rock p_1 , rock p_2 , rock p_3 , rock p_4 , rock p_5 , and rock p_6 are IV, III, III, III, IV, and III, respectively. Thus, we can conclude that the cloud model-based approach achieves transformation between qualitative and quantitative analysis. For example, the rockfall height of rock p_1 was 60 m, which should belong to III grade according to Table 1, and we obtained the results in rockfall height by the normal cloud generator: $\mu_I = 0$, $\mu_{II} = 0.0176$, $\mu_{III} = 0.0833$, $\mu_{IV} = 0.0002$. Therefore, the results by quantitative analysis are $\mu_{III} > \mu_{II} > \mu_{IV} > \mu_I$. Then we can come to the conclusion that rockfall height of rock p_1 more likely belongs to grade III, likely belongs to grade II, and almost impossibly belongs to grades I and IV, since the conclusion is consistent with the qualitative analysis.

Furthermore, by indicating the degree of certainty belonging to each risk level, the certainty degree provides more detailed information. For example, the level of rock p_3 is more likely to be III than the level of rock p_2 and rock p_6 , because the certainty degree of level IV of rock p_3 (0.4699) is higher than that of rock p_2 (0.4048) and rock p_6 (0.4355).

In this paper, the collected data are enough for the assessment. If the available information for the risk assessment is very limited in similar projects, probabilistic models, interval models, and imprecise probabilities should be considered [43-47]. Specifically, when all parameters are collected as random variables, probabilistic models are proposed; for cases in which all parameters are collected as interval variables, interval models have behaved with some favourable features; when parameters are described by random variables and interval parameters, respectively, imprecise probabilities with components of fuzzy set theory can be quite helpful. But the results are usually conservative as a result of the consideration of extreme events.

Generally speaking, results of five rocks (p_1, p_2, p_3, p_5, p_6) from the various methods are exactly the same, except for rock p_4 , because the methods for calculating the weight are different. Therefore, the data in Table 6 show high consistency of the results between the proposed

Table 6. Risk evaluation results of rockfall in tunnel portal section.

Rock	The integrated certainty degree				The normal cloud model method	AHP-FUZZY method	The ANN method
	M (I)	M (II)	M (III)	M (IV)			
p_1	0.0001	0.0782	0.4715	0.4864	IV	IV	IV
p_2	0.0735	0.2417	0.4048	0.0789	III	III	III
p_3	0.0002	0.0937	0.4699	0.1402	III	III	III
p_4	0.0742	0.2444	0.3802	0.1417	III	III	IV
p_5	0.0184	0.1556	0.4345	0.4817	IV	IV	IV
p_6	0.0016	0.2737	0.4355	0.0065	III	III	III

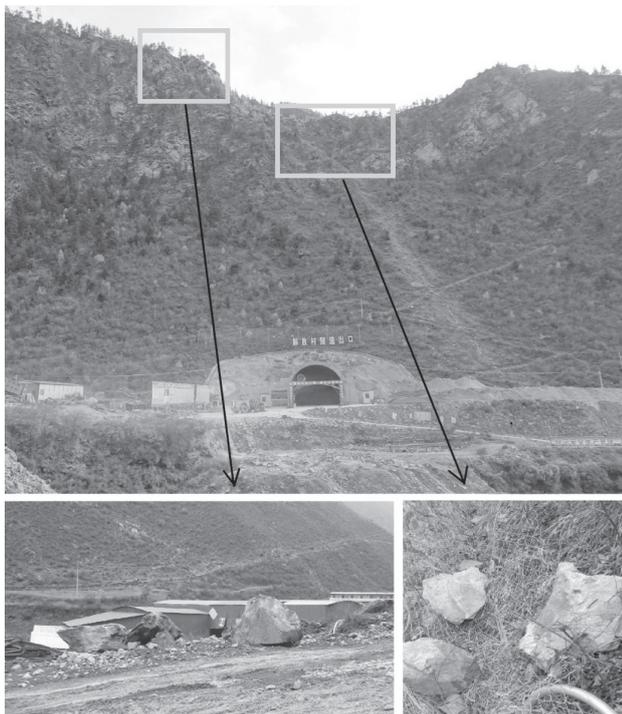


Fig. 6. Verification by practical situation.

normal cloud model and other two methods. Considering that the calculation of the proposed method is quicker and simpler, the normal cloud model method is better than AHP-FUZZY and artificial neural network methods.

During the construction of Jiefangcun Tunnel, rockfall occurred in the portal section. Rock p_1 and rock p_5 fall along the escarpment due to prolonged rain seriously interrupted traffic at the tunnel entrance. Moreover, some gravel around rock p_4 moved down the slope (Fig. 6). Fortunately, it did not cause any casualties. Therefore, the evaluation results obtained from the proposed method are generally in good agreement with the practical situation in Jiefangcun Tunnel.

Conclusions

Rockfall is a typical geological disaster in mountainous regions that is especially serious in southwestern China.

Based on normal cloud theory, in this paper a multi-index evaluation system is presented to systematically evaluate the risk of the rockfall hazards for tunnels in Sichuan Province.

Moreover, according to previous research and specific geological conditions, the potential dangers in the tunnel are classified into four ranks, and some geological factors such as rockfall shape and slope gradient are considered. In order to fully express the opinions of experts, the qualitative indices are quantified by continuous value scale, and the value of each index is determined by expert scoring. And then the weight of indices is rationally assigned by a simple dependent function. Finally, based on the three numerical characteristics calculated by the cloud generator algorithm with MATLAB, cloud drops were generated and the integrated certainty grades were determined.

The cloud model method was tested in rockfall cases in Jiefangcun Tunnel and the results by the present method are in good agreement with the practical situation. Moreover, the result is compared with those of AHP-FUZZY and artificial neural networks methods as well. In view of the fact that some potential rockfall is still perched on the slope above the portal section of Jiefangcun Tunnel, some proper rockfall protection designs should be applied to mitigate rockfall disasters, such as constructing protective wire nets and building rock fences.

Applying our findings to Jiefangcun Tunnel showed that the proposed method is feasible both in theory and practice. Thus, the cloud model-based method provides a practical guide on safe tunnel construction for similar projects. In this paper, we introduced the one-dimensional normal cloud model into rockfall risk assessment. Considering the successful application of the present model, two-dimensional and multi-dimensional cloud modeling strategies are worth exploring in rockfall risk assessment or other applications.

Acknowledgements

Much of the work presented in this paper was supported by the State Key Development Program for Basic Research of China (grant No. 2013CB036001) and the State Key Program of National Natural Science

of China (grant No. 51139004), National Natural Science Foundations of China (grant numbers 51379112 and 51422904), and Shandong Provincial Natural Science Foundation (grant number JQ201513). The authors would like to express appreciation to the reviewers for their valuable comments and suggestions that helped improve the quality of our paper.

References

1. YI Z. On the climatic uncertainty to the environment extremes: a Singapore case and statistical approach. *Polish Journal of Environmental Studies*, **24** (3), 1413, **2015**.
2. YOUSSEF A.M., PRADHAN B., AL-KATHERY M., BATHRELLOS G.D., SKILODIMOUS H.D. Assessment of rockfall hazard at Al-Noor Mountain, Makkah city (Saudi Arabia) using spatio-temporal remote sensing data and field investigation. *Journal of African Earth Sciences*, **101**, 309, **2015**.
3. SCHÖPA A., BAEWERT H., COOK K., MORCHE D. Recent rock fall activity in the Wetterstein Mountains revealed by a time series of terrestrial laser scans. *Mathematical Programming*, **119** (1), 169, **2009**.
4. CHOI Y., YOON S.Y., Park H.D. Tunneling Analyst: A 3D GIS extension for rock mass classification and fault zone analysis in tunneling. *Computers & Geosciences*, **35** (6), 1322, **2009**.
5. GORTMAKER S.L., MUST A., SOBOL A.M., PETERSON K., COLDITZ G.A. Assessment of Rockfall Hazard along the Road Cut Slopes of State Highway-72, Maharashtra, India. *Geomaterials*, **3** (1), **15**, **2013**.
6. CALCETTI F., PRISCO C.D. An Uncoupled Approach for the Design of Rockfall Protection Tunnels. *Structural Engineering International*, **19** (3), 342, **2009**.
7. RUNQIU H. Geo-engineering lessons learned from the 2008 Wenchuan earthquake in Sichuan and their significance to reconstruction. *Journal of Mountain Science*, **8**, 176, **2011**.
8. MENG X.L. Earthquake Disaster Characteristics of Tunnel 109 on Baoji-Chengdu Railway and Measures for Urgent Repair and Treatment. *Journal of Railway Engineering Society*, **6**, 91, **2009**.
9. FRATTINI P., CROSTA G., CARRARA A., AGLIARDI F. Assessment of rockfall susceptibility by integrating statistical and physically-based approaches. *Geomorphology*, **94** (3-4), 419, **2008**.
10. MICHOU D., DERRON M.H., HORTON P., JABOYEDOFF M., BAILLIFARD F.J., LOYE A., NICOLET P., PEDRAZZINI A., QUEYREL A. Rockfall hazard and risk assessments along roads at a regional scale: example in Swiss Alps. *Natural Hazards & Earth System Sciences*, **12**(3), 615, **2012**.
11. OKURA Y., KITAHARA H., SAMMORI T., KAWANAMI A. The effects of rockfall volume on runout distance. *Engineering Geology*, **58** (2) 109, **2000**.
12. LABIOUSE V. Fragmental rockfall paths: Comparison of simulations on Alpine sites and experimental investigation of boulder impacts. *Ninth International Symposium on Landslides*, 457, **2004**.
13. VOLKWEIN A., KLETTE J. Semi-Automatic Determination of Rockfall Trajectories. *Sensors*, **14** (10), 18187, **2013**.
14. VOLKWEIN A., KRUMMENACHER B., GERBER W., LARDON J., GEES F. Repeated controlled rockfall trajectory testing. EGU General Assembly Conference. EGU General Assembly Conference Abstracts, 17, **2015**.
15. LI Z.H., HUANG H.W., XUE Y.D., YIN J. Risk assessment of rockfall hazards on highways. *Georisk Assessment & Management of Risk for Engineered Systems & Geohazards*, **3** (3), 147, **2009**.
16. YE S., TANG H., CHEN H., ZHU H. Stability evaluation of rockfall based on AHP-Fuzzy method. *Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, **3**, 1369, **2010**.
17. GAO Y., DUAN Y.S., LIU J.W. Genetic strategy rough set of particle swarm optimization neural network application in collapse rockfall hazard risk assessment. *Journal of Highway and Transportation Research and Development*, **10** (1), 106, **2010**. [In Chinese].
18. FENG L., ZHU X., SUN X. Assessing coastal reclamation suitability based on a fuzzy-AHP comprehensive evaluation framework: A case study of Lianyungang, China. *Marine Pollution Bulletin*, **89** (1-2), 102, **2014**.
19. BAYRAM A., KANKAL M. Artificial Neural Network Modeling of Dissolved Oxygen Concentrations in a Turkish Watershed. *Polish Journal of Environmental Studies*, **24** (4), 1507, **2015**.
20. YE S., TANG H., CHEN H., ZHU H. Stability evaluation of rockfall based on AHP-Fuzzy method. *Seventh International Conference on Fuzzy Systems and Knowledge Discovery*, **3**, 1369, **2010**.
21. RUSSELL C.P., SANTI P.M., HUMPHREY J.D. Modification and Statistical Analysis of the Colorado Rockfall Hazard Rating System. *Engineering Geology*, **104** (1), 55, **2008**.
22. WANG X.L., FRATTINI P., CROSTA G. B., ZHANG L.Q., AGLIARDI F., LARI F., YANG Z.F. Uncertainty assessment in quantitative rockfall risk assessment. *Landslides*, **11** (4), 711, **2014**.
23. GENIŞ M., SAKIZ U., AYDINER B. Ç. A stability assessment of the rockfall problem around the Gökçöl Tunnel (Zonguldak, Turkey). *Bulletin of Engineering Geology & the Environment*, **1**, **2016**.
24. YE S.Q., CHEN H.K. The evaluation method for the hazard grading of the rockfall at the slope segment of the tunnel entrance. *China Railway Science*, **5**, 59, **2010** [In Chinese].
25. LI D., MENG H., Shi X. Membership clouds generators and membership cloud. *Journal of Computer Research & Development*, **32** (6), 15, **1995** [In Chinese].
26. LI D., Du Y. Artificial intelligence with uncertainty. *International Conference on Computer and Information Technology*, **15** (11), 2, **2004**.
27. WANG G., XU C., LI D. Generic normal cloud model. *Information Sciences*, **280**(280), 1, **2014**.
28. SUN X.X., CAI C., YANG J., SHEN, X.B. Route Assessment for Unmanned Aerial Vehicle Based on Cloud Model. *Mathematical Problems in Engineering*, **1**, **2014**.
29. ÉLISABETH RANISAVLJEVIĆ., DEVIN F., LAFFLY D., NIR Y.L. A dynamic and generic cloud computing model for glaciological image processing. *International Journal of Applied Earth Observation & Geoinformation*, **27** (4), 109, **2014**.
30. LIU J., WEN G., XIE Y.M. Layout optimization of continuum structures considering the probabilistic and fuzzy directional uncertainty of applied loads based on the cloud model. *Structural & Multidisciplinary Optimization*, **53** (1), 81, **2016**.
31. ZHANG X., LIU, Z., JIA C. A novel marine traffic safety assessment based on cloud models. *International Workshop on Education Technology & Computer Science. IEEE Computer Society*, 59, **2010**.

32. DU X.Y., YI Q.J., HUANG K.D., LIANG D.N. Transformation between qualitative variables and quantity based on cloud models and its application. *Systems Engineering & Electronics System*. **30** (4), 772, **2008**.
33. KAVOUSI-FARDA., NIKNAM T., FOTUHI-FIRUZABAD M. A novel stochastic framework based on cloud theory and h-modified bat algorithm to solve the distribution feeder reconfiguration. *IEEE Transactions on Smart Grid*, **99**, 1, **2015**.
34. LI Z., LIU Y. Single rule reasoning mapping for the two dimensional normal cloud model. *Caai Transactions on Intelligent Systems*. **5** (5), 464, **2010**.
35. PIERSON L.A., VICKLE R.V. Rockfall Hazard Rating System: Participant's Manual, Implementation, USA, 12, **1993**.
36. AN Y.I., PENG L.M., WU B. Comprehensive extension assessment on tunnel collapse risk. *Journal of Central South University*, **2**, 514, **2011**.
37. LI L., LIU L., YANG C., LI Z. The Comprehensive Evaluation of Smart Distribution Grid Based on Cloud Model. *Energy Procedia*, **17** (Part A), 96, **2012**.
38. WEN C. The extension set and non-compatible problems. *Advances in applied mathematics and mechanics in China*, **2**, 138, **1990**.
39. JIA C., XIAO S., LIU N. Application of extentic theory to evaluation of tunnel rock quality. *Chinese Journal of Rock Mechanics & Engineering*, **22** (5), 751, **2003**.
40. XIANG Z.Q. Preventive technology of unstable rock and rockfall hazard at tunnel entrance in high and steep slope. *Southwest Jiaotong University*, **2013** [In Chinese].
41. VALIRON G., COLLINGWOOD E.F. Applying Artificial Neural Networks for the Estimation of Chlorophyll-a Concentrations along the Istanbul Coast. *Polish Journal of Environmental Studies*, **23** (4), 1281, **2014**.
42. FARIS H., ALKASASSBEH M., RODAN A. Artificial Neural Networks for Surface Ozone Prediction: Models and Analysis. *Polish Journal of Environmental Studies*, **23** (2), 341, **2014**.
43. BEER M., YI Z., QUEK S.T., PHOON KK. Reliability analysis with scarce information: Comparing alternative approaches in a geotechnical engineering context. *Structural Safety*, **41** (3), 1, **2013**.
44. ZHANG H., DAI H., BEER M., WANG W. Structural reliability analysis on the basis of small samples: An interval quasi-Monte Carlo method. *Mechanical Systems & Signal Processing*, **37** (s1-2), 137, **2013**.
45. DEGRAUWE D., LOMBAERT G., DE ROECK G. Improving interval analysis in finite element calculations by means of affine arithmetic. *Computers & Structures*, **88** (3), 247, **2010**.
46. HANSS M., TURRIN S. A fuzzy-based approach to comprehensive modeling and analysis of systems with epistemic uncertainties. *Structural Safety*, **32** (6), 433, **2010**.
47. MÖLLER B., BEER M. Engineering computation under uncertainty-capabilities of non-traditional models, special issue on uncertainties in structural analysis. *Computers & Structures*, **86** (10), 1024-41, **2008**.