



Prediction of the Surrounding Rock Deformation Grade for a High-Speed Railway Tunnel Based on Rough Set Theory and a Cloud Model

Daohong Qiu¹ · Yang Liu¹ · Yiguo Xue¹ · Maoxin Su¹ · Ying Zhao¹ · Jiuhua Cui¹ · Fanmeng Kong¹ · Zhiqiang Li¹

Received: 12 October 2019 / Accepted: 1 October 2020 / Published online: 5 January 2021
© Shiraz University 2021

Abstract

With the continuous progress of the Chinese social economy, the construction of high-speed railways has been increasing in China. The deformation grade of surrounding rock plays an essential role in construction safety for high-speed railway tunnels. Therefore, predicting the deformation grade of surrounding rock during tunnel construction is of great significance. This paper takes the Zheng-Wan high-speed railway tunnel as the research object, and the Delphi method and cloud model theory are used to study the deformation of the rock surrounding the tunnel. The grade standard of the surrounding rock deformation for a high-speed railway tunnel is established, and the key factors affecting the deformation grade of the surrounding rock are analyzed. Then, rough set theory is used to obtain the weight of each influencing factor; in the weight calculation results, the occurrence of geological discontinuity and groundwater content account for the greatest weights, which are 0.42857 and 0.28571, respectively, in line with engineering practice. Finally, a model for predicting the deformation grade of surrounding rock is established by using cloud model theory, and the model results are compared with actual observations during tunnel excavation. The results show that this model offers effective operability, a high accuracy and an important value to engineering applications and guarantees tunnel safety during construction.

Keywords Deformation grade of surrounding rock · Delphi method · Rough set · Cloud model

1 Introduction

The utilization of high-speed railway tunnels is increasing in China to meet the growing infrastructure needs of residents. By the end of 2015, the total length of high-speed railway tunnels opened to traffic in China was approximately 3200 km, and the number of high-speed railway tunnels exceeded 2200. China has the most high-speed railway tunnels in the world (Zhao et al. 2017a, b). However, high-speed railway tunnel accidents occur all the time, so the safety of tunnel construction has become the top priority of high-speed railway tunnel engineering. Surrounding rock stability is important to guarantee safe and efficient construction. However, strict monitoring and accurate prediction

of surrounding rock deformation (Zhu and Su 2015) should be performed in any project.

There are various studies on tunnel displacement (Sun et al. 2018; Kong et al. 2019), and Li proposed a three-dimensional analytical model of blowout for a shallow tunnel in sand (Li et al. 2019). Fu used the modified Loganathan's formula, and a displacement field distribution prediction model was established (Fu et al. 2017). Wan proposed a new analytical model of loosening earth pressure in front of tunnel face (Wan et al. 2019). Zhang described the key influences of yaw excavation loadings on ground displacement and segmental stress for a curved shield tunnel (Zhang et al. 2020). At present, a variety of related research methods, mainly based on support vector machine (SVM), gray system, neural network and other theories, are applied to establish surrounding rock deformation prediction models. SVMs have the advantage of utilizing small sample sizes and nonlinear and high-dimensional pattern recognition. Yao et al. (2010) proposed a multistep advance prediction model for the displacement of rock surrounding a tunnel based on SVM. Hu et al. (2016) established a SVM model based on

✉ Yiguo Xue
xieagle@sdu.edu.cn

¹ Geotechnical and Structural Engineering Research Center, Shandong University, Jinan 250061, China

time series for the prediction of the deformation of rock surrounding a tunnel. However, the classic SVM algorithm gives only the binary classification, while in practical applications, solving the problem of multiclass classification is generally necessary. The gray system (GM) is suitable for situations in which few scattered samples are available and the data quality is poor. Lu adopted mathematical methods to improve the gray model and applied the model to the prediction of the deformation of rocks surrounding tunnels (Lu 2017). Neural networks are robust, and such predictive models can approach nonlinear problems. Li established a particle swarm optimization BP (PSO-BP) neural network by debugging and improving the prediction of surrounding rock deformation under complex geological conditions (Li et al. 2017). However, the neural network prediction results mainly depend on the accuracy of the samples. In addition, studies have been based on other methods (Weng et al. 2015; Zhang et al. 2019). Qiang proposed a multiscale nuclear limit learning machine prediction model for the deformation of rocks surrounding tunnels (Qiang et al. 2017). At present, many scholars have proposed a variety of surrounding rock deformation prediction methods; considering the diversity of high-speed railway tunnel construction and the complexity of geological conditions, each method has its limitations. In addition, most of the current studies focus on the prediction of surrounding rock deformation, while the prediction of the grade of tunnel deformation is less common.

In view of this situation, this paper studies the actual project of the Zheng-Wan high-speed railway tunnel in China. First, the deformation grade of the rock surrounding the tunnel is classified, and a standard of surrounding rock deformation grade suitable for high-speed railway tunnels is established. Then, the key factors affecting the deformation grade of the surrounding rock are analyzed, and the weight of each factor is obtained by using rough

set theory. Finally, the model of surrounding rock deformation grade prediction is established by using cloud model theory and is applied to engineering practice, and some useful conclusions are obtained.

2 Project Summary

2.1 Engineering Cases

The Zheng-Wan high-speed railway is an important part of the Zhengzhou-Chongqing high-speed railway. In this paper, 11 tunnels in section zwzq-6 (DK461 + 845.429–DK497 + 658.55) of the Zhengzhou-Wan high-speed railway are studied, in addition to 1 horizontal hole in Huang Jia Ditch and 1 inclined shaft in the Hou Ping tunnel. The studied tunnels are mainly distributed in Xiang Yang city, Nan Zhang County and Bao Kang County, as shown in Fig. 1.

2.2 Geology

The study area contains the Huang Ling anticline, the Jindou-Anzi village reversed anticline and the Shenlongjia and Jing Men platform fold belt of the upper Yangtze continental fold belt, with complex regional geological structures, including the Tian Jia ditch reverse fault, Kong Jia Fan fault and Xiang Er mountain branch fault. The tunnel is constructed by a bench cut method and had a vault collapse as shown in Fig. 2. The geological conditions of Zheng-Wan high-speed railway tunnel are complicated; in order to ensure the efficient and safe construction, it is necessary to predict the deformation grade of surrounding rocks in front of the palm face.

Fig. 1 Zheng-Wan high-speed railway route map

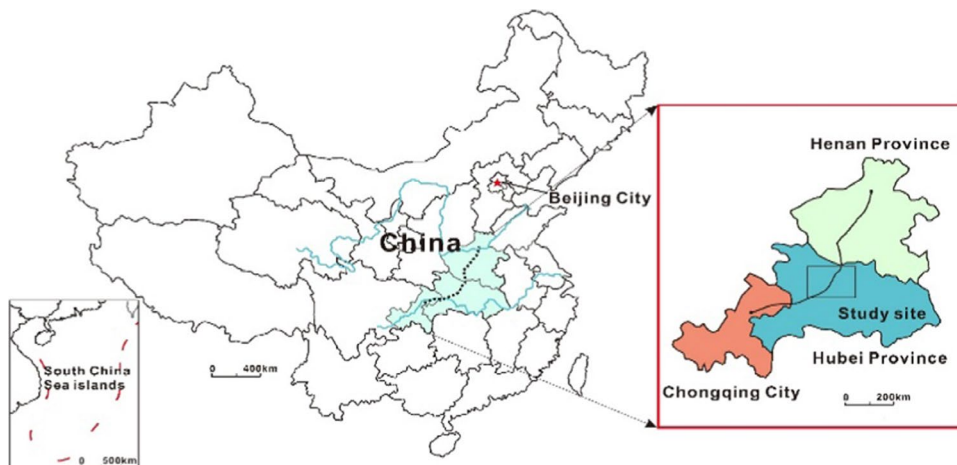


Fig. 2 Tunnel construction and vault collapse in the tunnel



3 Theoretical Method

3.1 Rough Set Theory

Rough set theory is a nonlinear mathematical method that was proposed by Polish scholar Pawlak (1982) and is used to process imprecise and incomplete information to discover hidden knowledge and reveal its potential rules (Zhang et al. 2011, 2009; Zhang et al. 2016a, b).

3.1.1 Decision Table and Dependence

If the decision table $S=(U, A)$ is an information system, then C and D included in A are two attribute subsets, which are called the conditional attribute and decision attribute, respectively. If these attributes meet the conditions

$$U/C = \{X_1, X_2, \dots, X_n\} \tag{1}$$

$$U/D = \{Y_1, Y_2, \dots, Y_m\}, \tag{2}$$

then the dependency of decision attribute D on conditional attribute C is defined as

$$K = \gamma_C(D) = \frac{1}{U} \sum_{i=1}^m |\gamma_C(D_i)|, \quad Y_i \in U/D \tag{3}$$

where $|\gamma_C(D_i)|$ is the sample compatible quantity. Clearly, $0 < K < 1$, and the closer the K is to 1, the higher the dependence of decision attribute D on conditional attribute C .

3.1.2 Weight Calculation Method

The rough set theory determines the weight calculation method as follows:

$$\gamma_C(D) = \frac{1}{U} \sum_{i=1}^m |\gamma_C(D_i)| \tag{4}$$

$$\gamma_{c-ci}(D) = \frac{1}{|U|} \sum_{i=1}^m |\gamma_{c-ci}(D_i)| \tag{5}$$

$$\omega_i = \frac{\gamma_C(D) - \gamma_{c-ci}(D)}{\sum_{i=1}^m [\gamma_C(D) - \gamma_{c-ci}(D)]} \tag{6}$$

where $\gamma_C(D)$ and $\gamma_{c-ci}(D)$ are the dependence of decision attribute D on conditional attribute C and the dependence of decision attribute D on conditional attribute $C-C_i$ after the evaluation index i is deleted, respectively; $|U|$ is the sample size; $|\gamma_C(D_i)|$ and $|\gamma_{c-ci}(D_i)|$ are the number of compatible samples in the decision table and the sample size in the decision table after the evaluation index i is deleted, respectively; and w_i is the index weight.

3.1.3 Applicability of the Rough Set Method

In this paper, the rough set method is used to calculate the weights of the influencing factors. Commonly used weight analysis methods include the analytic hierarchy process (AHP) and entropy weight method. The AHP is based on an in-depth analysis of nature, influencing factors and internal relations of complex decision-making problems, using less quantitative information to make the process of decision-making mathematical. (Xu et al. 2011; Zhao et al. 2017a, b) Thus, a simple decision method is provided for complex decision problems with multiple objectives, multiple criteria or no structural characteristics. The entropy weight method is an objective weighting method (Gao et al. 2018). In the specific application process, the entropy weight method is based on the variation degree of each index, and the entropy weight of each indicator is calculated by information entropy. Then, the weight of each index is modified by the entropy weight to obtain a more objective index weight. The data in this paper are actual engineering samples from the Zheng-Wan high-speed railway. The AHP is suitable for models and methods of making decisions in complex systems that are difficult to fully quantify. The sample values are taken from different sections, so the changes in each corresponding influencing factor are not uniform, and sudden

increases and decreases occur; the entropy weight method has some limitations for this kind of sample. The rough set method can determine rules for incomplete, uncertain and small sample data sets, and the weight of each influencing factor can be obtained through the analysis of attribute importance. Therefore, this paper appropriately adopts the rough set method to calculate the weights. The calculation results suggest that the largest weight corresponds to the structure surface behavior, followed by the groundwater content, which is in line with observations from actual engineering applications.

3.2 Cloud Model Theory

Cloud model theory was proposed by Li Deyi, an academician of the Chinese Academy of Engineering, and addresses the uncertain transformation model from a qualitative concept to a quantitative description (Li 2018; Zhang et al. 2016a, b).

3.2.1 Definition of Cloud

Definition of cloud: $X = \{x\}$ is a common set, and X is called the domain. The fuzzy set A exists in the domain X , the random number $\mu_A(x)$ with stable tendency exists for any element x , and x is called the membership degree of A .

Definition of normal cloud: Let X be the theoretical domain and C be the qualitative concept of the theoretical domain X supposing that the quantitative value $x \in X$ and x is a random implementation of the qualitative concept C ; if $x \sim N(E_x, E' n^2)$ is met, then $E' n \sim N(E_n, E2 e)$, where the determination of C is

$$\mu(x) = e^{-\frac{(x-E_x)^2}{2E_n^2}} \quad (7)$$

The distribution over the domain U is called the normal cloud.

3.2.2 Normal Cloud Model

The normal cloud model is the most basic and applicable cloud model (Mou and Cai 2018; Wang et al. 2015, 2017, 2018). The digital characteristics of the normal cloud are mainly represented by the expectation E_x , entropy E_n and hyper-entropy H_e .

3.2.3 Forward Cloud Generator and Computing

Forward normal cloud generator: If I defines the point x in the domain X , the cloud generator can generate the certainty distribution that x belongs to the qualitative concept C , and

the cloud generator at this time is called the forward cloud generator.

The forward cloud generator algorithm and calculation steps are as follows:

1. Calculate entropy E_n and hyper-entropy H_e according to the relevant data.
2. Based on the calculated entropy E_n and the hyper-entropy H_e , generate a normally distributed random number $E'_n \sim N(E_n, E_e^2)$.
3. Given the specific input value x and expected value E_x , use Eq. (1) to calculate the certainty:

$$\mu(x) = e^{-\frac{(x-E_x)^2}{2E_n^2}} \quad (8)$$

Determine the characteristics of the forward cloud model: According to the definition of the normal cloud model, the evaluation object factor can be used to calculate the cloud digital characteristics of the standard of a certain level according to the following equations:

$$E_x = \frac{B_{\min} + B_{\max}}{2} \quad (9)$$

$$E_{ni} = \frac{E_{x_{i+1}} - E_{x_i}}{3} \quad (10)$$

$$H_e = k \quad (11)$$

where k generally takes an empirical value and is 0.01 in this paper.

3.2.4 Normal Cloud Multi-index Comprehensive Probability Analysis

Normalize the certainty degree $\mu(x)$ of a single indicator at each level, and obtain a normalized certainty degree $\mu'(x)$. The comprehensive normal cloud certainty degree $\mu_k(x)$ for multiple indicators at each evaluation level can be determined by Eq. (12).

$$\mu_k(x) = \sum_{j=1}^m \mu'_j(x) w_j \quad (12)$$

where w_j is the weight of the j th indicator and satisfies $0 < w_j \leq 1$, $\sum_{j=1}^m w_j = 1$.

3.3 Delphi Method

The Delphi method (Wang et al. 2010), also known as the expert evaluation method, is a subjective prediction method. It asks for and aggregates expert opinions in written form;

the opinions of experts in the subject are collected and summarized and then shared back with them, in a method of clarifying and selecting the judgment given by an expert group on a problem for which accurate information is not readily available. The steps are as follows:

1. Determine the purpose of the investigation and select experts.
2. Design the evaluation consultation table.
3. Seek advice from experts and gather feedback.
4. Have the experts give a second judgment after reviewing the opinions.
5. Repeat steps (3) and (4) until broadly consistent results are achieved.
6. Obtain the results of data processing and weight determination.

4 Establishment of Rough Set and Cloud Model Prediction Model

4.1 Processes and Methods

4.1.1 Establishment Process

Based on the actual project of the Zheng-Wan high-speed railway tunnel in China, rough set theory is used to obtain the weight of each influencing factor. Finally, a model for predicting the deformation grade of surrounding rock is established based on the cloud model theory. The specific process is shown in Fig. 3.

4.1.2 Method Applicability

First of all, the rough set theory is applicable to tunnel engineering because its mathematical foundation is mature and no prior knowledge is required. Then, rough set theory is easy to use and it can deal with the inaccuracy of data. Rough set theory can process qualitative and quantitative data. The original data of tunnel engineering are complex

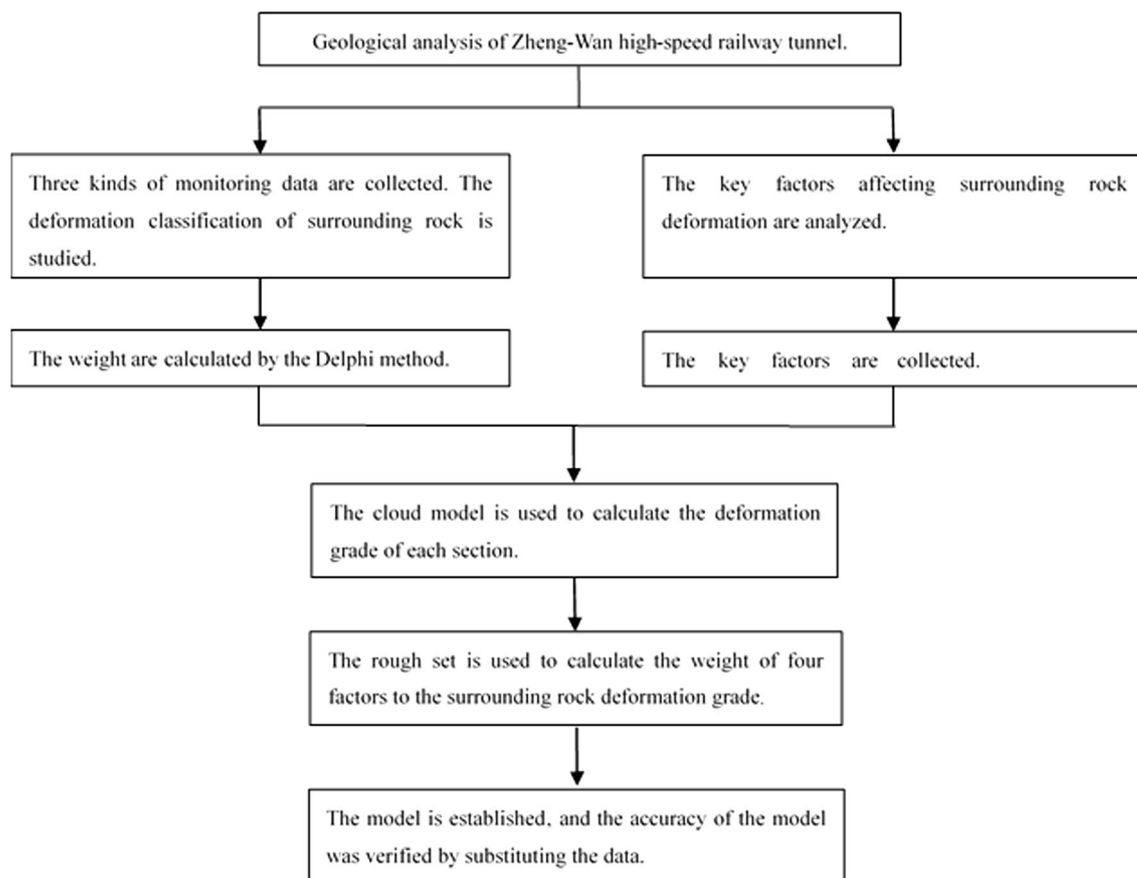


Fig. 3 Calculation flowchart

and diverse, so it is reasonable to adopt the rough set theory in this article. The cloud model theory reflects the uncertainty between qualitative and quantitative, especially the randomness and fuzziness. There are qualitative data in the original data collected in this article, and the cloud model can well realize the conversion between qualitative and quantitative. Therefore, it is reasonable to choose the cloud model theory in this article.

4.2 Classification of Surrounding Rock Deformation

According to the monitoring range of in situ vault settlement, the upper limit convergence and lower limit convergence were collected for the Zheng-Wan high-speed railway tunnel, and the degree of damage to the cavern caused by the deformation degree of the surrounding rock was observed. The classification criteria of this paper and the classification criteria of engineering specifications are different. This paper grades the surrounding rock deformation, not the surrounding rock. In addition, this article combines the single-factor method to grade the surrounding rock deformation according to the monitoring data of surrounding rock settlement and surrounding rock convergence of the Zheng-Wan high-speed railway tunnel. The monitoring values were divided into five ranges; the deformation degrees of surrounding rock corresponding to these five ranges were also used. Combined with the single-factor method, the surrounding rock deformation was divided into five grades: I, very little deformation; II, little deformation; III, moderate deformation; IV, major deformation; and V, intense deformation. The grade division of rock deformation around the high-speed railway tunnel and the range of the corresponding evaluation indexes are shown in Table 1.

4.3 Calculation of Surrounding Rock Deformation Grade

These three deformation indexes are obtained from the long-term deformation monitoring data from 20 sections along the Zheng-Wan high-speed railway tunnel. In the evaluation index system, each corresponding index has a rank interval,

Table 1 Ranges of the single-factor evaluation index grades

| Level | G/mm | i/mm | X/mm |
|-------|-------|-------|-------|
| I | 0–10 | 0–8 | 0–8 |
| II | 10–20 | 8–16 | 8–16 |
| III | 20–30 | 16–24 | 16–24 |
| IV | 30–40 | 24–32 | 24–32 |
| V | 40–50 | 32–40 | 32–40 |

(1) Vault settlement (G), (2) the upper limit convergence (S), (3) the lower limit convergence (X)

and the grade interval of the three deformation indexes is divided according to engineering practice and related deformation; the results are shown in Table 2. Dimensionless processing of the original data is conducted by considering the magnitude range of each evaluation index grade to normalize the index between 0 and 1. Specifically, the ratio of the index value to the whole interval value is calculated, and the dimensionless results are shown in Table 3. According to the cloud model calculation, since the magnitude ranges of the three indexes are the same, the index evaluation model for the three evaluation indexes is shown in Fig. 4.

The surrounding rock deformation is classified into three classification indexes, and the weights of the three indexes on the stability of the surrounding rock are obtained by the Delphi method. In this paper, the results calculated by Xue are applied (Xue et al. 2018). The calculation results are shown in Table 4.

Based on the normal cloud model, according to the sample data and Eqs. (1)–(3), entropy E_n and hyper-entropy H_e are calculated, with K equal to 0.01. Based on the calculated entropy E_n and the hyper-entropy H_e , a normally distributed random number $E' n \sim N(E_n, E2 e)$ is generated with the particular input value x and the expected value E_x ; Eq. (12) is used to calculate certainty. The level with the highest determination is the deformation grade of the surrounding rock of the tunnel section. The results of the surrounding rock deformation grades obtained are shown in Table 5.

4.4 Rough Sets are Used to Calculate Weights

4.4.1 Select Influencing Factors

The research object of this paper is a high-speed railway tunnel; according to the field investigation, part of the Zheng-Wan high-speed railway tunnel is affected by faults, and joints and fractures are extensively developed. Affected by groundwater, the self-stability of the surrounding rock is poor; therefore, the surrounding rock deformation is mainly affected by the surrounding rock strength and integrity and groundwater development. At the same time, considering the difficulty of data acquisition and the feasibility of practical engineering application (Panthee

Table 2 Dimension ranges of the single-factor evaluation index grades (dimensionless)

| Level | G/mm | S/mm | X/mm |
|-------|---------|---------|---------|
| I | 0–0.2 | 0–0.2 | 0–0.2 |
| II | 0.2–0.4 | 0.2–0.4 | 0.2–0.4 |
| III | 0.4–0.6 | 0.4–0.6 | 0.4–0.6 |
| IV | 0.6–0.8 | 0.6–0.8 | 0.6–0.8 |
| V | 0.8–1.0 | 0.8–1.0 | 0.8–1.0 |

Table 3 Tunnel deformation data samples from high-speed railway tunnels (dimensionless)

| Number | G/mm | S/mm | X/mm | Number | G/mm | S/mm | X/mm |
|--------|--------|--------|--------|--------|--------|--------|--------|
| 1 | 0.3960 | 0.2875 | 0.3150 | 11 | 0.4640 | 0.2100 | 0.2325 |
| 2 | 0.6520 | 0.3475 | 0.4200 | 12 | 0.5640 | 0.4950 | 0.3725 |
| 3 | 0.7780 | 0.6775 | 0.7500 | 13 | 0.7320 | 0.6325 | 0.6900 |
| 4 | 0.3200 | 0.1850 | 0.3425 | 14 | 0.1660 | 0.0850 | 0.1050 |
| 5 | 0.6520 | 0.4850 | 0.2625 | 15 | 0.3300 | 0.1975 | 0.2150 |
| 6 | 0.3220 | 0.3825 | 0.3700 | 16 | 0.2540 | 0.3000 | 0.2950 |
| 7 | 0.5500 | 0.3675 | 0.4350 | 17 | 0.6860 | 0.4575 | 0.5125 |
| 8 | 0.6100 | 0.4125 | 0.4950 | 18 | 0.9600 | 0.9225 | 0.8925 |
| 9 | 0.8160 | 0.7100 | 0.7525 | 19 | 0.8980 | 0.6350 | 0.6125 |
| 10 | 0.3100 | 0.3100 | 0.3425 | 20 | 0.2540 | 0.0900 | 0.1225 |

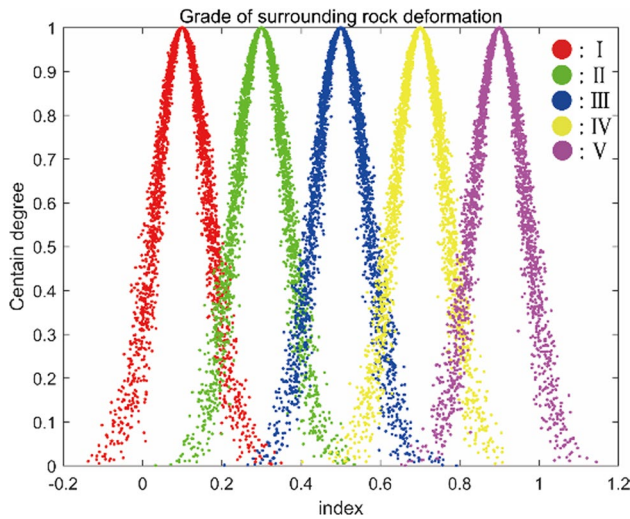


Fig. 4 Index evaluation results of the cloud model

Table 4 Weight of each evaluation factor

| Coefficient | G/mm | S/mm | X/mm |
|-------------|-------|-------|-------|
| a_1 | 10 | 7 | 8 |
| a_2 | 9 | 8 | 7 |
| a_3 | 10 | 7 | 8 |
| a_4 | 10 | 7 | 8 |
| E_i | 9.75 | 7.25 | 7.75 |
| δ^2 | 0.75 | 0.75 | 0.75 |
| W_i | 0.394 | 0.293 | 0.313 |

et al. 2016), when constructing the index evaluation system, more evaluation indexes are selected to reflect the above three aspects. The compressive strength of the rock reflects the general strength of the surrounding rock, the integrity coefficient and structure surface behavior of the rock reflect the integrity of the surrounding rock, and the groundwater content reflects the development of groundwater. Therefore, the selected evaluation indexes for the

Table 5 Calculation results

| Number | Deformation level | Number | Deformation level |
|--------|-------------------|--------|-------------------|
| 1 | 2 | 11 | 2 |
| 2 | 2 | 12 | 3 |
| 3 | 4 | 13 | 3 |
| 4 | 2 | 14 | 2 |
| 5 | 3 | 15 | 2 |
| 6 | 2 | 16 | 2 |
| 7 | 2 | 17 | 3 |
| 8 | 3 | 18 | 5 |
| 9 | 4 | 19 | 5 |
| 10 | 2 | 30 | 2 |

deformation of the rock surrounding the tunnel are the rock compressive strength, rock integrity coefficient, structure surface behavior and groundwater content.

1. Uniaxial compressive strength of rock: Rock is subjected to uniaxial compression until failure; the compressive strength of the rock is the load that a unit area of rock can withstand. The unit of compressive strength (R_c) is MPa.
2. Rock integrity coefficient: The rock integrity coefficient reflects the damage degree of the rock mass relative to intact rock and is used to determine an important indicator of rock mass quality. At present, the integrity of a rock mass is often measured by the integrity coefficient (K_v) of the rock mass under the domestic grading standards for surrounding rock.
3. The occurrence of geological discontinuity (S_1): This index includes the roughness of the geological discontinuity and the continuity and morphology of the rock wall.
4. Groundwater content: This index reflects the development of groundwater (W) in the surrounding rock. The unit of W is $(l \cdot (\text{min m})^{-1})$.

Table 6 Single-factor indicators

| Level | R_c (MPa) | K_v | S_1 | W ($l \cdot (\min m)^{-1}$) | |
|-------|-------------|----------|--|---------------------------------|----------|
| | | | | Description | Values |
| I | 80–120 | 0.75–1.0 | The structural surface is very rough and discontinuous. Closed palisades | 0–0.2 | 0–0.5 |
| II | 40–80 | 0.5–0.75 | Slightly rough; surface opening < 1 mm. Slightly weathered palisades | 0.2–0.4 | 0.5–1.0 |
| III | 20–40 | 0.35–0.5 | Slightly rough, surface opening < 1 mm. Severely weathered palisades | 0.4–0.6 | 1.0–2.5 |
| IV | 10–20 | 0.2–0.35 | Sliding surface or mud zone < 5 mm thick or with an opening 1–5 mm. Continuous | 0.6–0.8 | 2.5–12.5 |
| V | 5–10 | 0–0.2 | Soft clay zone > 5 mm thick or with an opening > 5 mm | 0.8–1.0 | 12.5–∞ |

Table 7 Decision table of factors influencing high-speed railway tunnel deformation

| Number | R_c | K_v | S_1 | W | Level | Number | R_c | K_v | S_1 | W | Level |
|--------|-------|-------|-------|-----|-------|--------|-------|-------|-------|-----|-------|
| 1 | 2 | 2 | 3 | 2 | 2 | 11 | 2 | 2 | 2 | 2 | 2 |
| 2 | 3 | 3 | 3 | 3 | 2 | 12 | 2 | 3 | 3 | 3 | 3 |
| 3 | 3 | 4 | 4 | 3 | 4 | 13 | 3 | 4 | 4 | 3 | 3 |
| 4 | 2 | 2 | 2 | 2 | 2 | 14 | 2 | 2 | 2 | 1 | 2 |
| 5 | 2 | 3 | 2 | 3 | 3 | 15 | 2 | 2 | 2 | 2 | 2 |
| 6 | 2 | 2 | 2 | 2 | 2 | 16 | 2 | 2 | 1 | 2 | 2 |
| 7 | 2 | 3 | 3 | 4 | 2 | 17 | 3 | 3 | 3 | 3 | 3 |
| 8 | 3 | 3 | 4 | 3 | 3 | 18 | 4 | 5 | 5 | 5 | 5 |
| 9 | 4 | 4 | 4 | 4 | 4 | 19 | 4 | 4 | 5 | 4 | 5 |
| 10 | 2 | 2 | 2 | 2 | 2 | 20 | 2 | 2 | 1 | 1 | 2 |

Table 8 Dependence, importance and weight of each influencing factor

| Factors | R_c | K_v | S_1 | W |
|------------|---------|---------|---------|---------|
| Dependence | 0.75 | 0.75 | 0.65 | 0.70 |
| Importance | 0.05 | 0.05 | 0.15 | 0.1 |
| Weight | 0.14286 | 0.14286 | 0.42857 | 0.28571 |

4.4.2 Constitute the Decision Table

Because the rough set program of MATLAB software can deal with only discrete data, the data obtained in the actual project should be discretized. According to the magnitude range or value of each conditional attribute, each single-factor index is classified, as shown in Table 6.

According to Table 6, the original data are discretized, taking the influence factors after discretization as conditional attributes, as shown in Table 7.

4.4.3 Weight of Influencing Factors

According to the decision table of factors influencing tunnel deformation, the rough set program of MATLAB software is used to calculate the dependence, importance and weight of each influencing factor on the deformation grade of the rock surrounding the tunnel, as shown in Table 8.

4.5 Model Establishment

Using the cloud model program of MATLAB software, the cloud model method is adopted to establish the prediction model for the surrounding rock deformation grade. The established model uses only the engineering data obtained from the actual project through advanced detection as input; that is, the four influencing factors can determine the prediction of the surrounding rock deformation grade. Ten other sections are selected to predict the deformation grade of the surrounding rock and compare the results with the actual situation.

According to the actual monitoring of the Zheng-Wan high-speed railway tunnel, the sample data from 10 tunnel sections are collected. In the evaluation system, each influencing factor or an evaluation index has a quantitative value range for each grade, as shown in Table 6. Dimensionless processing is carried out for the data shown in Table 6, and the results are given in Table 9. The sample data are nondimensionalized by considering the magnitude range of the single-factor evaluation index grade, as shown in Table 9, and the results are shown in Table 10. According to the cloud model theory, the index evaluation models of the four influencing factors are shown in Fig. 5.

Table 9 Scale ranges of single-factor evaluation indexes (dimensionless)

| Number | R_c | K_v | S_1 | W |
|--------|---------------|----------|---------|-----------|
| I | 0.6522–1 | 0.75–1 | 0–0.2 | 0–0.02 |
| II | 0.3043–0.6522 | 0.5–0.75 | 0.2–0.4 | 0.02–0.04 |
| III | 0.1304–0.3043 | 0.35–0.5 | 0.4–0.6 | 0.04–0.1 |
| IV | 0.0435–0.1304 | 0.2–0.35 | 0.6–0.8 | 0.1–0.5 |
| V | 0–0.0435 | 0–0.2 | 0.8–1 | 0.5–1 |

Table 10 Monitoring data samples from the high-speed railway tunnel (dimensionless)

| Number | R_c | K_v | S_1 | W |
|--------|-------|-------|-------|-------|
| 1 | 0.148 | 0.18 | 0.62 | 0.68 |
| 2 | 0.409 | 0.25 | 0.45 | 0.064 |
| 3 | 0.087 | 0.25 | 0.70 | 0.312 |
| 4 | 0.391 | 0.65 | 0.18 | 0.028 |
| 5 | 0.365 | 0.40 | 0.50 | 0.084 |
| 6 | 0.365 | 0.47 | 0.22 | 0.032 |
| 7 | 0.2 | 0.37 | 0.42 | 0.052 |
| 8 | 0.443 | 0.72 | 0.36 | 0.024 |
| 9 | 0.097 | 0.45 | 0.25 | 0.076 |
| 10 | 0.093 | 0.30 | 0.85 | 0.4 |

4.6 Model Inspection

Based on the cloud model theory and the weights calculated by the sample monitoring values and the rough set method, the determination degree of each grade in the 10 sections is calculated, and the predicted surrounding rock deformation grades of the 10 sections are obtained and compared with the actual surrounding rock deformation grade. The results are shown in Table 11.

According to the above prediction results, the predicted values of 8 out of the 10 sections are consistent with the actual values. No. 4 tunnel section and No. 6 tunnel section have made support in advance in order to ensure the stability of surrounding rocks, so the predicted results of the No. 4 tunnel section and No. 6 tunnel section are lower than the actual deformation grades, but the predicted values are close to the actual value. Therefore, this model is feasible for predicting the deformation grade of rock surrounding a high-speed railway tunnel, which also confirms the reliability of the weight of each influencing factor obtained above. In addition, the deformation anomaly of a tunnel section was discovered in time during the excavation process through on-site monitoring and measurement; if the deformation situation and surrounding rock deformation level can be predicted before excavation to provide an early warning, measures will be taken in advance; meanwhile, the stability of the tunnel will be better controlled.

Such a prediction can also save time, improve efficiency and reduce cost. Therefore, the establishment of a prediction model for the surrounding rock deformation grade of high-speed railway tunnels has great engineering application value.

5 Discussion

5.1 Comparison of Cloud Model Theory and BP Neural Network Method

To verify the applicability of the cloud model theory, the sample data are taken as the training sample. The neural network method (Shi et al. 2016) and SVM method (Chen 2015) are used to teach this sample, and the prediction model for surrounding rock deformation grade is established and verified (Table 11). A comparison between the results of the two methods and the cloud model is shown in Table 12.

The calculation results of the prediction model established by the BP neural network are different from the actual results in 4 tunnel sections. These differences show that the learning accuracy of the neural network is dependent on sample size and that small samples lead to some limitations in learning. The SVM method resulted in 7 tunnel sections that deviate from the actual results, and its prediction accuracy is only 30%, indicating that the computational accuracy of the SVM for multiclass classification problems needs to be improved. The cloud model exhibits better accuracy and higher engineering application value.

5.2 Discussion on Portability of Models

In this paper, based on the Zheng-Wan high-speed railway tunnel, the prediction model of surrounding rock deformation grade of high-speed railway tunnel is established. The model established in this paper is only applicable to Zheng-Wan high-speed railway, for the following reasons. First of all, this article selects the influence factors of surrounding rock deformation which are Zheng-Wan high-speed railway tunnel influential factors, these factors may not apply to other tunnels, and then, this article is based on Zheng-Wan settlement of high-speed railway tunnel surrounding rock and convergence data of surrounding rock deformation of surrounding rock classification, so the model for the other tunnel is not feasible. However, the methods, ideas and conclusions of this paper can provide some references for other tunnel projects.

6 Conclusions

1. This paper takes the Zheng-Wan high-speed railway tunnel as the research object. Based on rough set theory and cloud model theory, a deformation grade predic-

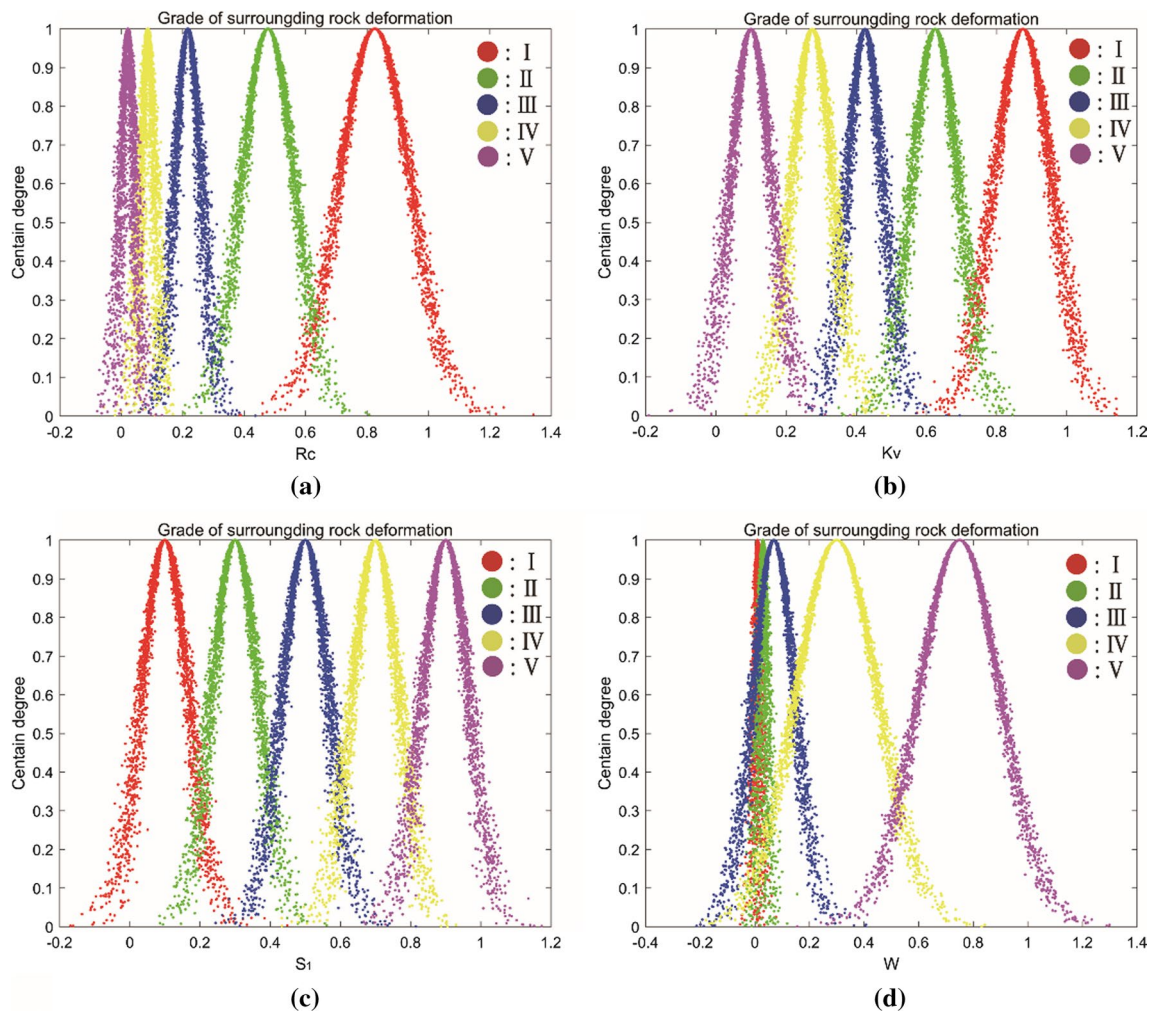


Fig. 5 a The cloud model of R_c . b The cloud model of K_v . c The cloud model of S_1 . d The cloud model of W

Table 11 Comparison table of model test

| Number | Certainty of each level | | | | | Predicting level | Actual level |
|--------|-------------------------|----------------|-----------------|-----------------|-----------------|------------------|--------------|
| | I | II | III | IV | V | | |
| 1 | 1.96E-12 | 0.009868 | 0.657716 | 0.012051 | 0.093003 | III | III |
| 2 | 0.278476 | 0.2013 | 0.520276 | 2.39E-10 | 1.45E-07 | III | III |
| 3 | 0.004456 | 0.276563 | 0.396422 | 0.202002 | 0.025924 | III | III |
| 4 | 0.497156 | 0.20632 | 0.033136 | 1.84E-08 | 3.10E-21 | I | II |
| 5 | 0.339013 | 0.164212 | 0.502991 | 1.48E-27 | 1.36E-42 | III | III |
| 6 | 0.765611 | 0.15862 | 0.118294 | 3.10E-19 | 3.16E-09 | I | II |
| 7 | 0.257822 | 0.493403 | 0.466129 | 2.39E-18 | 8.70E-47 | II | II |
| 8 | 0.237029 | 0.186447 | 0.265376 | 7.84E-81 | 4.08E-37 | III | III |
| 9 | 0.766551 | 0.132602 | 0.232386 | 0.007407 | 0.017423 | I | I |
| 10 | 0.001578 | 0.210291 | 0.324339 | 1.91E-11 | 0.000818 | III | III |

The data in bold indicate that the predicted result is inconsistent with the actual situation. Display the number using an exponential representation, replacing part of the number with $E+n$, where E (for the exponent) means multiplying the preceding number by 10 to the n TH power

Table 12 Comparison of calculation results

| Number | Results of cloud model | Results of neural network method | Results of support vector machine method | Actual level |
|--------|------------------------|----------------------------------|--|--------------|
| 1 | III | III | II | III |
| 2 | III | III | II | III |
| 3 | III | IV | II | III |
| 4 | I | II | II | II |
| 5 | III | III | II | III |
| 6 | I | III | II | II |
| 7 | II | III | II | II |
| 8 | III | III | II | III |
| 9 | I | II | II | I |
| 10 | III | III | II | III |

The data in bold indicate that the predicted result is inconsistent with the actual situation

tion model for high-speed railway tunnels is established. First, the tunnel deformation grade is classified and studied, and the deformation grade standard for the high-speed railway tunnel is established. The key factors affecting the deformation grade of the surrounding rock are analyzed, and the correlation between the deformation grade and influencing factors is established. Finally, cloud model theory is introduced to predict the deformation grades of tunnel sections. The application results show that the predictions of the model are consistent with the actual situation. This method has important value for engineering applications, can provide a certain reference for the stability analysis of surrounding rock and can guarantee the safe construction of a tunnel.

2. Rough set theory is adopted to determine the weight of each evaluation index, and the weight problem is transformed into an important evaluation problem regarding attributes in the rough set. This method requires no prior experience; the solution process is completely driven by the actual sample and has effective operability. Considering the randomness of the cloud model theory, when processing small sample data sets, some test samples should be retained, and repeated tests should be conducted to obtain the prediction model with the highest accuracy.

Acknowledgements Most of the research work in this paper was funded by the National Natural Science Foundation of China (Grant Nos. 41772298, 51309144, 41877239) and the Central University and Foundation for Basic Research (Grant No. 2018 jc044).

References

Chen HS (2015) Prediction and analysis of displacement and deformation of surrounding rock based on support vector machine. Chongqing Jiaotong University, Chongqing

- Fu HL, Zhang JB, Huang Z, Shi Y, Wang J, Xing XS (2017) Prediction and analysis of ground displacement and stress caused by the excavation of a shallow-buried shield tunnel in a compound stratum. *Modern Tunnel Technol* 54(4):97–106
- Gao CL, Li SC, Wang J, Li LP, Lin P (2018) The risk assessment of tunnels based on grey correlation and entropy weight method. *Geotech Geol Eng* 36(3):1621–1631
- Hu J, Wang KK, Dong JH (2016) Application of cultural fish swarm optimization support vector machine in deformation prediction of tunnel surrounding rock. *Road* 3:221–225
- Kong F, Lu D, Du X, Shen C (2019) Displacement analytical prediction of shallow tunnel based on unified displacement function under slope boundary. *Int J Numer Anal Methods Geomech* 43(1):183–211
- Li K (2018) Research on classification method of surrounding rock based on entropy weight-cloud model. *Modern Tunnel Technol* 55(04):69–86
- Li PF, Zhao Y, Zhou XJ (2016) Displacement characteristics of high-speed railway tunnel construction in loess ground by using multi-step excavation method. *Tunn Undergr Space Technol* 51:41–55
- Li HB, Zhai QZ, Zhang Y, Wang YW, Zhang X (2017) Application of PSO-BP neural network in prediction of tunnel rock deformation. *Subgrade Eng* 5:164–169
- Li PF, Chen KY, Wang F, Li Z (2019) An upper-bound analytical model of blow-out for a shallow tunnel in sand considering the partial failure within the face. *Tunn Undergr Space Technol* 91:102989
- Lu W (2017) Application of GM (1, 1) model to deformation prediction of Feng Shan tunnel. *Archit Technol* 9:025
- Mou RF, Cai QJ (2018) Stability evaluation for the surrounding rock structure based on the normal cloud model and the rough set theory. *J Saf Environ* 18(04):1251–1257
- Panthee S, Singh PK, Kainthola A, Singh TN (2016) Control of rock joint parameters on deformation of tunnel opening. *J Rock Mech Geotech Eng* 8(4):489–498
- Qiang Y, Li SH, Liu CQ (2017) Deformation prediction for a tunnel rock mass based on the multi-scale combination Kernel extreme learning machine model. *Modern Tunnel Technol* 54(6):70–76
- Shi JX, Zhang CL, Lv WQ, Wang ZL (2019) Prediction of surrounding rock deformation based on BP neural network. *China Water Transp* 17(08):300–347
- Sun HS, Wang LW, Chen YD, Dong Y, Zhang JH, Sun WB (2018) Nonlinear analysis of tunnel deformation and mechanisms of stress transfer caused by basement excavation. *Soil Mech Found Eng* 55(5):298–304

- Wan T, Li P, Zheng H, Zhang M (2019) An analytical model of loosening earth pressure in front of tunnel face for deep-buried shield tunnels in sand. *Comput Geotech* 115:103170
- Wang YC, Sun HY, Shang YQ, Zhu M (2010) Classification of surrounding rock based on Delphi method and ideal point method. *Chin J Geotech Eng* 32(04):651–656
- Wang YC, Jing HW, Zhang Q, Yu LY, Xu ZM (2015) A normal cloud model-based study of grading prediction of rockburst intensity in deep underground engineering. *Rock Soil Mech* 36(4):1189–1194
- Wang XT, Li SC, Ma XY, Xue YG, Hu J, Li ZQ (2017) Risk assessment of rockfall hazards in a tunnel portal section based on normal cloud model. *Polish J Environ Stud* 26(5):2295–2306
- Wang XT, Li SC, Xu ZH, Hu J, Pan DD, Xue YG (2018) Risk assessment of water inrush in karst tunnels excavation based on normal cloud model. *Bull Eng Geol Environ* 78:3783–3798
- Weng MJ, Hu B, Jou Y, Liao C (2015) Deformation analysis of tunnel excavation in gravelly formation using the anisotropic degradation model. *J Chin Inst Eng* 38(8):1–9
- Xu ZH, Li SC, Li LP, Hou JG, Sui B, Shi SS (2011) Risk assessment of water or mud inrush of karst tunnels based on analytic hierarchy process. *Rock Soil Mech* 32(06):1757–1766
- Xue YG, Zhang XL, Li SC, Qiu DH, Su MX, Li LP, Li ZQ, Tao YF (2018) Analysis of factors influencing tunnel deformation in loess deposits by data mining: a deformation prediction model. *Eng Geol* 232:94–103
- Yao BZ, Yang CY, Yao JB, Sun J (2010) Tunnel surrounding rock displacement prediction using support vector machine. *Int J Comput Intell Syst* 3(6):843–852
- Zhang P, Chen JP, Qiu DH (2009) Evaluation of tunnel surrounding rock quality with extenics based on rough set. *Rock Soil Mech* 30(01):246–250
- Zhang P, Chen JP, Xiao YH, Zhao AP (2011) Application of rough set-wavelet neural network to tunnel surrounding rock classification. *Chin J Underg Space Eng* 7(3):429–456
- Zhang QH, Xie Q, Wang GY (2016a) A survey on rough set theory and its applications. *Control Theory Appl* 16(2):323–333
- Zhang Y, Shi SW, He JD (2016b) Application of cloud model to engineering geology classification of surrounding rock mass of tunnel. *J Eng Geol* 24(03):339–344
- Zhang XL, Xue YG, Qiu DH, Yang WM, Su MX, Li ZQ, Zhou BH (2019) Multi-Index classification model for loess deposits based on rough set and BP neural network. *Polish J Environ Stud* 28(2):953–963
- Zhang MJ, Li SH, Li PF (2020) Numerical analysis of ground displacement and segmental stress and influence of yaw excavation loadings for a curved shield tunnel. *Comput Geotech* 118:103325
- Zhao BJ, Kong DK, Tan ZS (2017a) Yichang—Wan Zhou railway tunnel disease evaluation system based on analytic hierarchy process. *China Civ Eng J* 50(S2):243–248
- Zhao Y, Tian Y, Sun Y (2017b) Development and planning of high-speed railway tunnels in China. *Tunnel Constr* 37(01):11–21
- Zhu HB, Su W (2015) Analysis of tunnel deformation influence factors based on high-speed railway tunnels. *China Civ Eng J* 48(S1):306–310