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SHAP Parameter Sensitivity Analysis of Rock Mechanics Parameters

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ABSTRACT

Accurate determination of the rock mass's mechanical parameters directly affects engineering projects' safety and cost-effectiveness. Based on an extensive literature review, a dataset containing 318 sets of rock mass parameters is compiled to support our research. Key rock-mass descriptors—Q, RMR, GSI, UCS, the rock material constant m_i, and the disturbance factor D—are first standardized to mitigate scale effects. A correlation-coefficient matrix is then computed and visualized with a heatmap to quantify inter-variable relationships. The results indicate a strong positive correlation between Q and RMR and a moderate negative correlation between m_i and D. Some mechanical variables show near-unity positive correlations with indicators such as RMR and UCS, suggesting highly consistent trends. Pairwise distribution analyses further reveal an approximately linear relationship between GSI and RMR, a logarithmic tendency between Q and RMR, and clustered patterns in the m_i–D space, implying potential multicollinearity and nonlinear interactions.

KEYWORDS

Rock mass mechanical parameters; Data sample; Algorithm.

1. INTRODUCTION

Engineering rock mass refers to rock mass in the field of rock engineering, which mainly includes underground engineering rock mass, sloping rock mass, and dam foundation rock. As well as the discrepancies in the development of structural planes within the rock mass, the mechanical properties of the rock mass are very complex. Accurate determination of mechanical parameters directly affects the safety and reasonableness of construction costs.

Since Vernadsky [1], a Russian investigator in the 18th century proposed a five-level rock state classification, dozens of engineering rock mass classification methodologies have been established to evaluate rock mass stability and determine support methods. At present, the common approaches for evaluating and classifying rock mass quality can be displayed in the following. Deere [2] proposed the rock quality designation index (RQD), which divided the rock mass quality grade by the integrity of the drilling core in 1964. In 1974, based on the RQD, Barton et al. [3] proposed a Q classification system with six parameters: RQD, structural plane roughness coefficient, structural plane group alteration coefficient, groundwater reduction coefficient, and stress intensity reduction coefficient. Bieniawski [4] also suggested a rock mass rating (RMR) classification method based on the RQD, which takes in rock strength, joint spacing, groundwater conditions, and joint direction. In 1994, Hoek and Brown [5]) based on a large amount of rock test data, through the analysis of these data, summed up the geological strength index method, the so-called GSI rock mass classification approach. In addition, rock mass quality evaluation and classification methods with strong influence also include mining rock mass rating (MRMR) classification [6], slope mass rating (SMR) classification [7], and Chinese slope mass rating (CSMR) classification [8]. However, the complex mechanical properties of rock masses and the reliance on human experience in traditional theories could create challenges, particularly when dealing with large volumes of data. This dependence not only lessens efficiency but also increases the likelihood of human error.

This study selected three representative empirical formulas for rock mechanics parameters, and used 318 sets of rock mechanics parameters to conduct a correlation analysis of these parameters, aiming to reveal the relationships among rock mechanics parameters.

2. TRADITIONAL ROCK QUALITY EVALUATION METHODS

The Q system is an approach for classifying rock mass quality, proposed by Barton and coworkers in 1974 based on the RQD, and is extensively utilized at present. Initially aimed at determining support schemes during tunnel construction, after long-term development and improvement, it has also been broadly applied in the classification of surrounding rock in underground caverns, rock mass quality classification of rock foundations, and rock mass quality classification of high steep slope hydropower engineering. The calculation formula for the Q value reads:

$$Q = \frac{RQD}{J_n} \cdot \frac{J_r}{J_a} \cdot \frac{J_w}{\mathrm{SRF}} \tag{1}$$

Where RQD represents the rock quality index, J_n denotes the number of joint sets, J_r is the joint roughness coefficient, J_a signifies the joint alteration impact coefficient, J_w is the joint water reduction coefficient, and SRF stands for the stress reduction factor.

The RMR evaluation system is a rock mass quality grading approach proposed by Bieniawski [4] who summarized more than 300 tunnel projects. The RMR method includes six indicators for scoring each rock mass stability factor, and the sum of various scores represents the RMR. The value of rock mass, RMR formula, is given as follows:

$$T_{RMR} = A + B + C + D + E + F \tag{2}$$

Where T_{RMR} denotes the total score of the RMR method; A is the strength score of complete rock material; B represents the rock drilling coring quality score; C signifies the joint spacing score; D is the joint state score; E represents the groundwater state score; F denotes the relationship between the occurrence of structural plane and the direction of engineering.

The Hoek-Brown criterion represents an empirical criterion utilized for describing the strength and deformation properties of rock materials, proposed by South African rock mechanics experts Evert Hoek and John Bray in 1980. This criterion was subsequently improved many times to form the generalized Hoek-Brown criterion as follows:

$$\sigma_1 = \sigma_3 + \sigma_{ci}\left(\frac{m_b \sigma_3}{\sigma_{ci}} + s\right)^a \tag{3}$$

Where σ_1 and σ_3 signify the maximum principal stress and the minimum principal stress of rock mass at failure, respectively. σ_{ci} represents the uniaxial compressive strength of intact rock; m_b, s, and a signify the material constants related to rock mass properties, which can be converted into functions of GSI and D. Their corresponding formulas can be provided by:

$$
\begin{gathered}
m_b = m_i \exp\left(\frac{GSI-100}{28-14D}\right) \\
s = \exp\left(\frac{GSI-100}{9-3D}\right) \\
a = 0.5\left[\exp\left(-\frac{GSI}{15}\right) - \exp\left(-\frac{20}{3}\right)\right] / 6
\end{gathered}
\tag{4}
$$

Where GSI stands for a geological strength index, which reflects the weakening degree of rock mass strength by various geological conditions from two aspects: the structural characteristics of rock mass and the surface condition of joints. The rock material constant (m_i) can be determined by performing a triaxial test on the intact rock samples. Factor D represents a disturbance factor, which reflects the disturbance degree of rock mass due to blasting and stress relaxation, and the corresponding value varies from 0 to 1.

3. DATA ACQUISITION AND DATA CLEANING

3.1. Data Acquisition and Data Cleaning

Our dataset comprises 318 sets of rock mass parameters sourced from published literature [10-18]. According to various types of data sources, they were divided into four categories: tunnel engineering (A, 58 cases), slope engineering (B, 65 cases), underground coal mine engineering (C, 116 cases), and other geotechnical engineering (D, 79 cases). These various categories include a wide range of factors and indicators, including the rock uniaxial compressive strength (UCS), geological strength index (GSI), rock material constant (m_i), disturbance factor (D), RMR score (RMR), and Q score (Q). The statistical parameters of different characteristics are presented in Table 1, and the corresponding box diagram is illustrated in Figure 1. The meter character in Fig. 1 indicates the abnormal value or extreme situation, the horizontal solid line in the box indicates the median, the red dot indicates the mean value, and the upper and lower horizontal lines at the boundary of the box represent the third and first quarter points, respectively.

Table 1 provides essential statistical parameters of rock mass evaluation indicators across a wide range of geotechnical engineering categories. The statistical distribution reveals distinct geomechanical characteristics among the four engineering types. As is seen, tunnel engineering exhibits superior rock mass quality with higher Q scores, RMR scores, and GSI values. Conversely, underground coal mine engineering demonstrates significantly deteriorated rock mass conditions, indicating highly fractured and weaker rock masses. The uniaxial compressive strength values follow a similar pattern, with tunnel engineering exhibiting the highest mean value and underground coal mine engineering exhibiting the lowest. These systematic variations in geomechanical properties across engineering types provide critical insights for developing robust prediction algorithms capable of accommodating diverse rock mass conditions encountered in practical geotechnical applications.

Figure 1 illustrates the statistical distribution characteristics of various rock mass evaluation indicators through box plot analysis. The presented distributions demonstrate noticeable heterogeneity in geomechanical properties, particularly in Q scores for tunnel engineering applications where values span over two orders of magnitude. The RMR score distributions also reveal smaller interquartile ranges for slope engineering compared to tunnel projects, indicating more consistent discontinuity conditions in slope applications. Additionally, the GSI distributions follow similar patterns to RMR, confirming the rational theoretical correlations between these two classification systems. The notable outliers in UCS and m_i values, particularly in underground coal mining applications, highlight potential challenges in parameter estimation for exceptional geological conditions. These distribution characteristics informed our selection of machine learning algorithms capable of handling both the central tendencies and the extreme values encountered in diverse geotechnical engineering contexts.

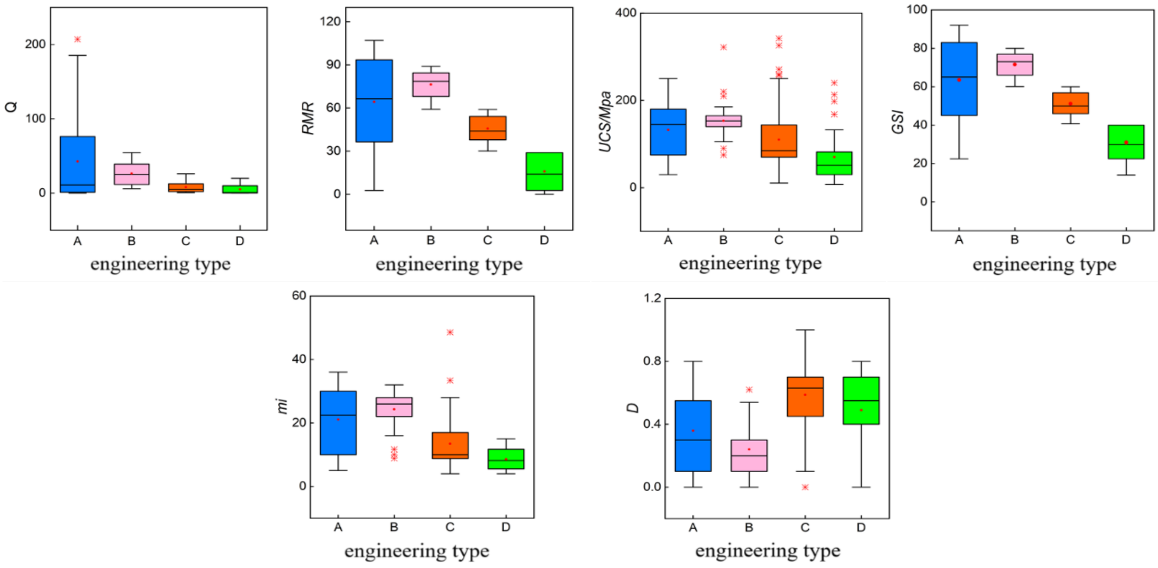

Figure 1. Box plots of various rock mass evaluation indicators in the dataset

Table 1. Statistical parameters of various rock mass evaluation indicators in the rock mass

Engineering type	Value type	Q	RMR	GSI	m_i	D	UCS (MPa)
A	Maximum	207	107	92	36	1	326
	Minimum	0.18	11.8	28.51	5	0	30
	Mean	69.04	78.42	72.95	25.4	0.34	160.67
	Standard deviation	60.52	27.36	18.24	10.05	0.24	63.96
B	Maximum	119	99.5	87	34	1	257
	Minimum	0.09	3	22.5	5.2	0.2	30
	Mean	17.06	62.41	62.27	19.73	0.35	130.4
	Standard deviation	19	22.33	15	7.72	0.24	47.24
C	Maximum	55	89	80	48.56	0.8	260
	Minimum	0.04	5	14	4	0.2	10.44
	Mean	2.32	36	45	12.46	0.5	96.53
	Standard deviation	5.37	16.67	11.35	6.65	0.24	58.43
D	Maximum	133	101	88	35	0.8	271
	Minimum	0.12	6.5	25	4	0.3	17.3
	Mean	20.36	60	60.56	17.62	0.38	125.3
	Standard deviation	28.88	24.1	16.05	9.11	0.26	60.53

3.2. Data Cleaning

To ensure the prediction effectiveness, data cleaning is a crucial step that addresses errors, missing, incomplete, and redundant data in the dataset to enhance data accuracy, reliability, and practicality. Some of the vacancy values are supplemented by referring to the RMR and GSI conversion formula proposed by Hoek and Brown [5] and the GSI and Q conversion formula proposed by Hoek et al [9]. The specific formulas are as follows:

$$GSI = \mathrm{RMR}_{89} - 5 \tag{5}$$

$$GSI = 9\ln(Q) + 44 \tag{6}$$

The six selected features in geotechnical engineering cases are all numerical data, and the value ranges of different features are different, and even the order of magnitude may be different. To obtain accurate classification results and to ensure the role of each feature, the features are standardized to reduce the effect of scale and feature dimension on the model. In the present investigation, the StandardScaler approach is adopted. The specific implementation algorithm is to subtract the mean and divide the standard deviation, so that each feature in the dataset possesses a mean of zero and a standard deviation of one, to ensure that the features are on the same scale.

Four categories of geotechnical engineering data are relatively unbalanced in the collected dataset. The number of examples of tunnel engineering (A, 58 cases), slope engineering (B, 65 cases), and other geotechnical engineering (D, 79 cases) is remarkably less than that of underground coal mining engineering (C, 116 cases). When encountering unbalanced datasets, the most common machine learning algorithms could not achieve good results. This is essentially attributed to the fact that most machine learning models tend to predict the majority class to minimize the error rate. During the training process, the model often learns the features of the majority class while neglecting the features of the minority class. This results in the model having poor recognition ability for the minority class.

After careful consideration of various sampling methods, random oversampling is methodically chosen for the present investigation instead of approaches like SMOTE (synthetic minority over-sampling technique) or adaptive sampling. This choice is based on three key advantages; First, random oversampling maintains data authenticity by preserving actual rock mass parameters, while other methods may generate synthetic samples that deviate from physical reality. Second, it ensures model reliability by retaining the original data distribution characteristics without introducing artificial patterns that could increase prediction uncertainty. Third, its computational simplicity and result traceability make it more practical for engineering applications.

To implement this approach, a small number of samples are randomly copied to increase their frequency until achieving a balanced distribution across a vast range of geotechnical engineering categories. To ensure model generalizability and prevent overfitting, the balanced dataset is randomly mixed and divided into training and test sets in a 7:3 ratio, with the random seed set to 0.8 during segmentation to ensure reproducible results.

4. SHAP PARAMETER SENSITIVITY ANALYSIS

The SHAP sensitivity analysis results demonstrate clear physical rationality in how various factors contribute to rock mass mechanical parameters. The corresponding specific procedures of such an analysis are provided in the following.

For rock mass uniaxial compressive strength (σ_{cmass}), the *UCS* parameter exhibits the highest influence at 28.33%, highlighting its role as the core parameter in rock mass strength calculation. The *GSI* indicator (20.44%) and Q score (20.54%) demonstrate similar and significant influences, reflecting the deterministic role of rock mass structural characteristics on strength. The rock constitutive parameter m_i (10.18%) has relatively less influence, whereas the disturbance factor *D* (2.68%) demonstrates a minimal impact.

Regarding rock mass deformation modulus (E_m), *GSI* dominates with 38.28%, confirming that the degree of joint development is crucial in determining rock mass deformation capability. The significant influences of *Q* (28.98%) and *RMR* (25.58%) further validate the practicality of rock mass classification systems in evaluating deformation modulus. The minor influences of *UCS* (2.35%) and m_i (1.09%) align with the theory that the deformation modulus is primarily controlled by structure.

For cohesion (C), UCS holds absolute dominance at 61.16%, indicating that cohesion primarily originates from the bonding strength of the rock material itself. The Q score (12.18%) and GSI indicator (10.50%) follow, suggesting limited weakening effects of structural planes on cohesion. The parameters m_i (3.90%) and D (3.59%) exhibit the minimal influence.

Concerning the internal friction angle (ϕ), the rock type parameter (m_i) contributes the most (38.58%), emphasizing its importance in controlling shear strength. In addition, the GSI indicator (16.59%) and Q score (16.00%) exhibit similar influences, reflecting the significant impact of the structural planes on the friction angle. The disturbance factor (D) (13.21%) also demonstrates a higher influence compared to other parameters, indicating substantial effects of this on the joint surface friction characteristics. The minor influence of the UCS factor (3.92%) corresponds to the indirect influence of the intact rock strength on the friction angle.

Overall, the SHAP analysis results somehow confirm the consistency among the influencing factors of the rock mass mechanical factors and the theoretical models, providing a reliable theoretical basis for rock mass engineering parameter prediction.

Table 2. SHAP parameter sensitivity.

Parameter	σ_{cmass}	Em	C	ϕ
UCS	28.33%	2.35%	61.16%	3.92%
Q	20.54%	28.98%	12.18%	16.00%
GSI	20.44%	38.28%	10.50%	16.59%
RMR	17.83%	25.58%	8.66%	11.71%
m_i	10.18%	1.09%	3.90%	38.58%
D	2.68%	3.72%	3.59%	13.21%

5. CONCLUSION

This study compiled a literature-based dataset of 318 rock-mass cases and investigated the inter-relationships among key descriptors (Q, RMR, GSI, UCS, m_i, and disturbance factor D) to support reliable prediction of rock-mass mechanical parameters. Missing values were supplemented using commonly adopted conversions, and all features were standardized to remove scale effects. SHAP-based sensitivity analysis provides an interpretable assessment of factor contributions, showing that UCS dominates cohesion (61.16%) and is also the most influential factor for rock-mass compressive strength, GSI contributes most to the deformation modulus E_m (38.28%), mi is the primary contributor to ϕ (38.58%), and D has a non-negligible influence on ϕ (13.21%). Overall, the combined correlation and SHAP analyses yield physically consistent insights and provide a practical basis for feature selection and robust, interpretable prediction of rock-mass mechanical parameters.

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