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# Machine Learning-Based Blasting Design for Predicting Specific Charge in Tunnel Construction

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## Abstract

This study developed a machine learning model for predicting the specific charge in cut area of tunnel blast designs using data collected from 18 tunnel construction sites. Input variables included round length, number of charge holes per area, excavation section coefficient, cross-sectional area, maximum and minimum spacing of cut holes, blast cut type, explosive type, RMR, maximum overburden depth, and rock type.

Nine different machine learning models were applied and compared: Linear Regression (LR), Lasso Regression, Ridge Regression, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forest (RF), Light Gradient Boosting Machine (LightGBM), Histogram-based Gradient Boosting (HGB), and Artificial Neural Network (ANN). The Random Forest model showed the best performance with an $R^2$ of 0.852 and RMSE of 0.082 on test data.

SHAP value importance analysis revealed that blast cut type was the most influential factor (importance score: 0.1627), followed by minimum spacing (0.0393) and maximum spacing (0.0170). Through the developed model, customized blasting designs can be applied to various geological conditions in tunnel construction sites, significantly enhancing the efficiency and safety of tunnel construction projects.

## Keywords

Tunnel Blasting, Specific Charge, Cut Area, Machine Learning, SHAP Analysis

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# 1 Introduction

The efficiency and accuracy of blasting operations in tunnel construction significantly impacts the overall efficiency, safety, and cost of a project. The goal of tunnel blasting operations is to maximize blasting efficiency while minimizing vibrations and noise through precise design. To achieve this, key design factors such as specific charge, drilling layout and spacing, types of explosives, and cut blasting methods must be comprehensively considered. Among these, specific charge is a critical factor in blasting design, calculated as the total weight of explosives used divided by the total volume of rock to be fragmented. It directly affects rock fragmentation and fly rock distance, playing a vital role in determining optimal design conditions and calculating total blasting costs. Moreover, accurate prediction of specific charge reduces secondary blasting costs caused by inadequate fragmentation and optimizes energy distribution to enhance fragmentation efficiency (Choi et al., 2009; Kahriman et al., 2001).

Tunnel blasting is carried out with a single free face, where the rock is initially confined, and a second free face is created during the process, fracturing the rock and propelling it away from the free face (Min et al., 2005). Cut blasting is the first step in the tunnel blasting process and plays a critical role in influencing all subsequent blasting operations, ultimately determining the success of tunnel excavation in terms of advance rate, fragmentation, and vibration control. The initial cut area, having only a limited free face, requires a higher specific charge and the strongest explosives compared to other zones.

However, the complex conditions of tunnel construction sites often make it challenging to apply uniform blasting designs, necessitating customized designs that account for specific geological and environmental characteristics. To address these challenges, recent studies have actively explored the use of various machine learning models, a branch of artificial intelligence (AI) capable of training on complex data patterns to make predictions, for specific charge estimation in tunnel blasting design.

Previous research has explored various approaches to specific charge prediction. For instance, Alipour et al. (2012) developed a model combining Artificial Neural Networks (ANN) and Multiple Variable Linear Regression Analysis (MVLRA) to predict specific charge in railway tunnel blasting in Taiwan. In a subsequent study, Alipour et al. (2021) applied the Support Vector Machine (SVM) algorithm for specific charge prediction, while Taiwo et al. (2024) conducted research using Decision Tree models to predict specific charge for blasting operations.

However, most previous studies have focused on predicting the overall specific charge for tunnel blasting, which limits their applicability to the cut area of tunnel blasting. Additionally, according to Jong and Lee (2004), tunnel blasting has traditionally relied heavily on the experience of blasting engineers, with designs varying based on geological conditions that influence specific charge.

Therefore, this study aims to develop a quantitative machine learning model for predicting specific charge in cut area of tunnel construction projects. To achieve this, data from 18 tunnel blasting projects were analyzed to identify key factors influencing specific charge, and various machine learning algorithms were applied to derive the optimal predictive model.

# 2 Research Methodology

## 2.1 Data Collection

This study collected data from 18 tunnel construction projects, comprising a total of 208 datasets. For tunnel blast design analysis, eleven critical variables were selected for determining specific charge in cut area. During the data collection process, missing or erroneous data points caused by manual input errors or omissions were identified and removed to ensure data quality.

Based on the tunnel blasting design data, eleven input variables were used for specific charge prediction. Round length represents the advance length per blast cycle. Number of charge holes per area indicates total number of blast holes divided by face area. Excavation section coefficient is calculated using Eq. (1), considering round length and cross-sectional area.

$$\text{Excavation section coefficient} = \left( 1 + \frac{L}{\sqrt{A}} \right)^2 \tag{1}$$

Where $L$ Round Length (m)
$A$ Cross-Sectional Area ($m^2$)

Cross-sectional area refers to the area of tunnel face. Maximum and minimum spacing in cut area represent the largest and smallest distances between adjacent blast holes, respectively. Blast cut type indicates the pattern used (Cylinder-cut, V-cut, Double V-cut), while types of explosives are categorized as dynamite, emulsion, or high-performance emulsion. RMR (Rock Mass Rating) provides geomechanical classification of rock mass quality. Maximum overburden depth measures the greatest vertical distance from ground surface to tunnel. Rock type classification is based on geological characteristics. The dataset covers diverse geological conditions and construction scenarios, with rock grades ranging from I to V according to RMR classification. Data collection focused particularly on the cut area characteristics, as this zone typically requires higher specific charge and has significant influence on overall blast performance.

### 2.2 Model Development and Evaluation

For the development of specific charge prediction model, data preprocessing was first conducted. Categorical data including blast cut type, rock type, and types of explosives were transformed into unique binary vectors using the One-Hot Encoding technique. Numerical data were normalized to a range of [0, 1] using the Min-Max Scaling technique.

Nine different machine learning models were developed in this study. First, linear regression-based models - Linear Regression (LR), Lasso Regression (Lasso), and Ridge Regression (Ridge) - were implemented to analyze linear relationships between variables, with regularization techniques applied to prevent overfitting. Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) models were employed to account for nonlinearity in the data. Additionally, ensemble models including Random Forest (RF), Light Gradient Boosting Machine (LightGBM), and Histogram-based Gradient Boosting (HGB) were developed to combine the results of multiple learners. Finally, an Artificial Neural Network (ANN) model was structured to learn complex nonlinear relationships.

The dataset was split into training data (70%) and test data (30%) for model development. The Grid Search technique was used for hyperparameter optimization to achieve optimal model performance. To enhance model reliability, 5-fold cross-validation was implemented, where the dataset was divided into five folds with each fold used once as validation data.

For model assessment, the coefficient of determination ($R^2$) and root mean squared error (RMSE) were selected as performance metrics. SHAP (SHapley Additive exPlanations) analysis was incorporated to evaluate the relative importance of input variables in model predictions.

## 3 Data Analysis

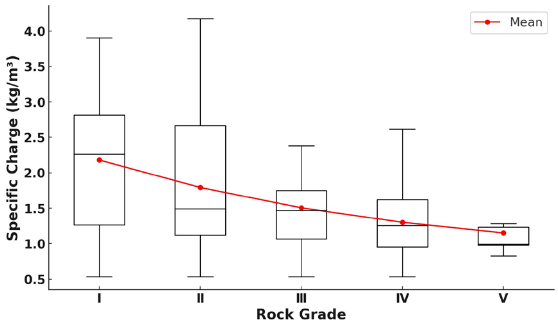
### 3.1 Analysis of Input Variables

Analysis of the collected data revealed distinct patterns in blasting design parameters across different rock grades. These patterns provide insights into how design parameters vary with rock mass conditions.

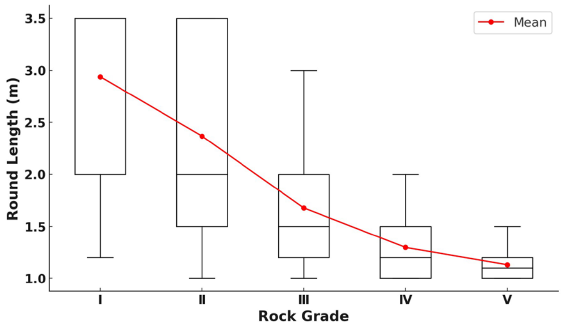
The specific charge distribution displays a clear relationship with rock grade (Fig. 1(a)). For rock grade I, specific charge ranges from 1.2 to 2.8 kg/$m^3$ (average 2.1 kg/$m^3$), while grade V shows a more concentrated range of 1.0-1.3 kg/$m^3$ (average 1.1 kg/$m^3$). This relationship reflects the mechanical properties of the rock mass, where stronger rocks require higher explosive energy for effective fragmentation.

Round length exhibits similar behavior, as shown in Fig. 1(b), ranging from 2.0-3.5 m in grade I to 1.0-1.2 m in grade V. The number of charge holes per unit area displays an opposite trend (Fig. 1(c)), increasing from 1.7 holes/$m^2$ in grade I to 2.2 holes/$m^2$ in grade V, with greater variance in lower rock grades.

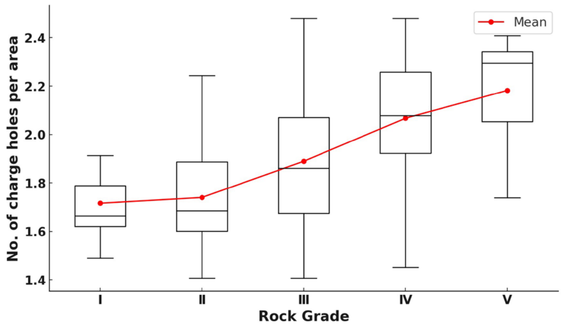
Design pattern analysis revealed systematic adaptations to rock conditions (Fig. 2). The Cylinder-cut method was predominantly used in higher rock grades (63.2% in grade I), while V-cut becomes prevalent in lower grades (62.5% in grade IV). Explosive selection similarly shows systematic variation, with high-performance explosives preferred in higher grades (60.5% in grade I) and standard emulsion explosives becoming dominant in lower grades (100% in grade V).




(a)

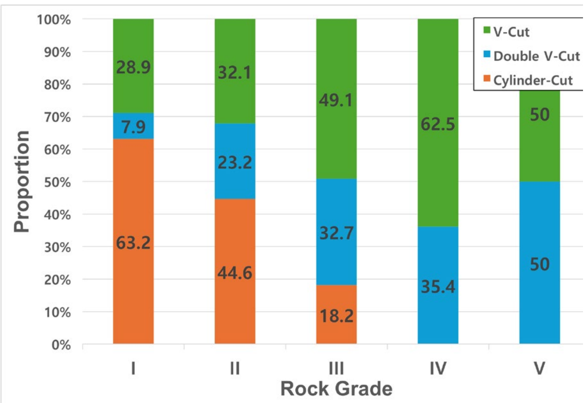



(b)

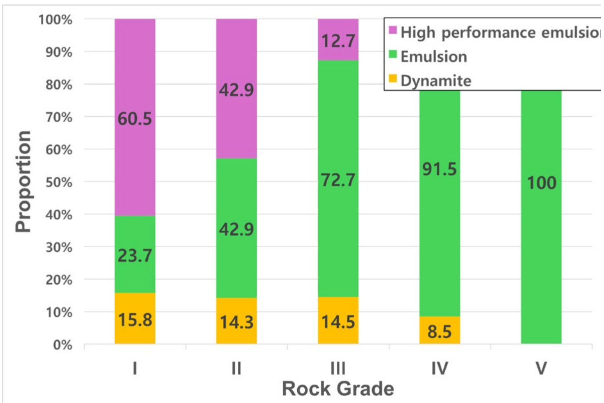



(c)

Fig. 1 Distribution analysis of blast design parameters according to rock grade: (a) Specific charge, (b) Round length, (c) Number of charge holes per area




(a)




(b)

Fig. 2 Statistical analysis of blasting design patterns according to rock grade: (a) Distribution of blast cut type, (b) Distribution of explosive type

## 3.2 Model Performance Analysis

The performance of machine learning models was evaluated using the coefficient of determination ($R^2$) and root mean squared error (RMSE), with results summarized in Table 1. The evaluation metrics were calculated through 5-fold cross-validation and testing to assess both predictive accuracy and model stability.

Ensemble-based models demonstrated consistently superior performance compared to other approaches. The RF model achieved the highest $R^2$ (0.852 ± 0.076) and lowest RMSE (0.082 ± 0.020) on test data, while maintaining strong performance on training data ($R^2$: 0.985 ± 0.072, RMSE: 0.079 ± 0.018). This indicates robust predictive capability and good generalization. Other ensemble methods, HGB and LightGBM, showed similar but slightly lower performance levels, with test $R^2$ values of 0.846 ± 0.077 and 0.840 ± 0.078, respectively.

Traditional linear regression models (LR, Ridge, Lasso) showed relatively lower performance, with test $R^2$ values around 0.75, suggesting nonlinear relationships between input variables and specific charge. SVM and KNN models demonstrated moderate performance levels (test $R^2$: 0.783 and 0.798, respectively), while the ANN model performed similarly to linear models (test $R^2$: 0.755 ± 0.091), indicating that neural network complexity did not provide significant advantages for this prediction task.

Table 1 Performance comparison of machine learning models

| **Model** | **Training** | | **Test** | |
|---|---|---|---|---|
| | **$R^2$ (mean ± std)** | **RMSE (mean ± std)** | **$R^2$ (mean ± std)** | **RMSE (mean ± std)** |
| LR | 0.762 ± 0.089 | 0.124 ± 0.031 | 0.751 ± 0.092 | 0.127 ± 0.033 |
| Lasso | 0.759 ± 0.085 | 0.125 ± 0.030 | 0.748 ± 0.090 | 0.128 ± 0.032 |
| Ridge | 0.761 ± 0.087 | 0.124 ± 0.031 | 0.750 ± 0.091 | 0.127 ± 0.033 |
| SVM | 0.795 ± 0.082 | 0.115 ± 0.028 | 0.783 ± 0.085 | 0.118 ± 0.030 |
| KNN | 0.812 ± 0.079 | 0.110 ± 0.026 | 0.798 ± 0.083 | 0.114 ± 0.028 |
| RF | 0.985 ± 0.072 | 0.079 ± 0.018 | 0.852 ± 0.076 | 0.082 ± 0.020 |
| LightGBM | 0.972 ± 0.074 | 0.083 ± 0.021 | 0.840 ± 0.078 | 0.086 ± 0.023 |
| HGB | 0.976 ± 0.073 | 0.082 ± 0.020 | 0.846 ± 0.077 | 0.085 ± 0.022 |
| ANN | 0.768 ± 0.088 | 0.123 ± 0.031 | 0.755 ± 0.091 | 0.126 ± 0.032 |

The prediction performance of the RF model is visualized in Fig. 3, where predicted values are plotted against actual specific charge values. The scatter plot shows strong agreement between predicted and actual values for both training and test datasets, with points closely following the ideal prediction line (y=x). This visualization confirms the model's consistent performance across the range of specific charge values encountered in the dataset.

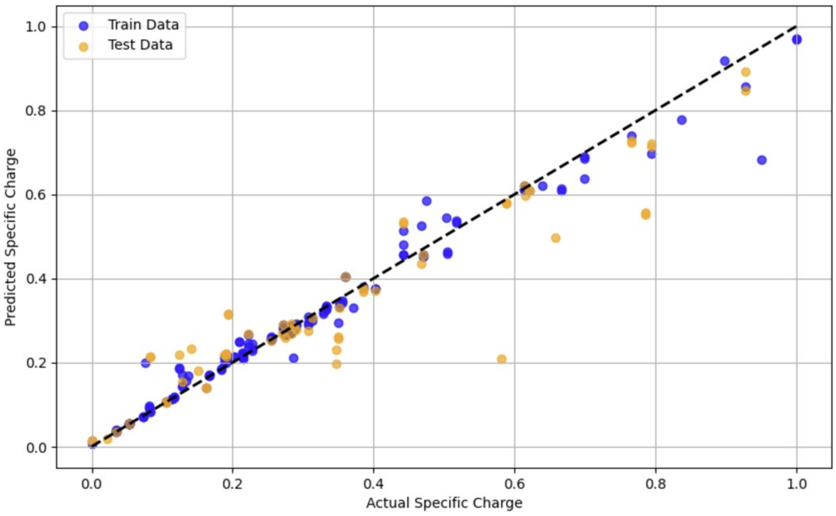



Fig. 3 Comparison of actual and predicted specific charge using RF model

The small standard deviations across all performance metrics suggest stable model behavior, with ensemble methods showing particularly consistent performance across different data splits.

## 3.3 Variable Importance

SHAP (SHapley Additive exPlanations) analysis was conducted to evaluate the relative importance of input variables in the RF model's prediction of specific charge. Fig. 4 presents the Mean Absolute SHAP values for each input variable, providing a quantitative measure of their contribution to the model predictions.

The analysis revealed that blast cut type was the most critical variable in predicting specific charge, with a Mean Absolute SHAP Value of 0.1627, significantly higher than other variables. This finding indicates that the selection of blast cut pattern has the greatest influence on specific charge determination. The second and third most important variables were minimum spacing (0.0393) and maximum spacing (0.0170). These results highlight the importance of spacing conditions as key design parameters, with minimum spacing showing notably higher importance than maximum spacing in determining specific charge.

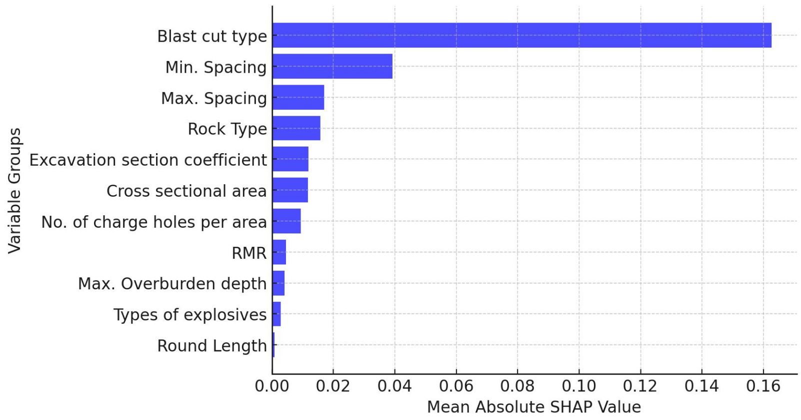



Fig. 4 Group SHAP value importance analysis for specific charge prediction using RF

Rock type showed a moderate influence with a value of 0.0157, confirming that geological characteristics affect explosive quantity requirements. The excavation section coefficient, cross-sectional area, and number of charge holes per area recorded values of 0.0119, 0.0117, and 0.0094 respectively, indicating their moderate impact on specific charge prediction.

Variables such as RMR (0.0045), maximum overburden depth (0.0041), types of explosives (0.0029), and round length (0.0008) showed relatively lower importance values. This suggests that while these parameters are necessary for comprehensive tunnel design, their direct influence on specific charge determination in the cut area is comparatively minor.

These findings provide valuable insights for prioritizing design considerations in tunnel blasting, particularly emphasizing the critical role of blast cut type selection and spacing configuration in determining specific charge.

# 4 Results and Discussion

The analysis results demonstrate that the RF model provides reliable predictions of specific charge in cut area, with an $R^2$ of 0.852 and RMSE of 0.082. This performance level suggests that machine learning approaches, particularly ensemble methods, can effectively capture the complex relationships between geological conditions and blasting design parameters.

The variable importance analysis through SHAP values reveals that geometric design factors, particularly cut type and spacing, have the strongest influence on specific charge prediction. This finding aligns with practical experience where blast geometry plays a crucial role in determining explosive requirements. The relatively lower importance of parameters such as RMR and overburden depth suggests that while these factors influence overall tunnel stability, their direct impact on cut area specific charge is limited.

The systematic variation of design parameters across rock grades, as shown in the input variable analysis, reflects current industry practices. The transition from Cylinder-cut to V-cut methods and from high-performance explosives to standard emulsion explosives in lower rock grades demonstrates how blasting designs adapt to changing geological conditions. This adaptation is also evident in the complementary relationship between round length and charge hole density.

The model's performance characteristics suggest potential applications in preliminary blasting design, particularly in estimating initial specific charge values for cut areas. However, the model should be considered a design aid rather than a replacement for engineering judgment, as site-specific conditions and practical constraints may require adjustments to the predicted values.

# 5 Conclusions

This study developed a machine learning-based approach for predicting specific charge in tunnel blast design, with the following key findings:

1. The Random Forest model demonstrated superior predictive performance among nine machine learning algorithms, achieving an $R^2$ of 0.852 and RMSE of 0.082 on test data. This performance level indicates the model's potential as a practical tool for preliminary blast design.

2. Blast cut type emerged as the most influential factor in specific charge prediction (SHAP value: 0.1627), followed by minimum spacing (0.0393) and maximum spacing (0.0170). This hierarchy of importance provides guidance for prioritizing design parameters.

3. Analysis of input variables revealed systematic relationships between rock grade and design parameters, including specific charge, round length, and blast hole density. These relationships provide valuable insights into how blasting design adapts to varying geological conditions.

The developed model demonstrates the potential of machine learning approaches in optimizing tunnel blast design, particularly in the critical cut area. While the model serves as a valuable tool for initial design estimation, final designs should incorporate site-specific considerations and engineering expertise.

## Acknowledgements

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