The 2025 World Congress on
Advances in Structural Engineering and Mechanics (ASEM25)
BEXCO, Busan, Korea, August 11-14, 2025

Prediction of charging density by blasting zones in tunnel excavation using machine learning

Jung In Kwon[1)], Ho Seong Lee[2)], and *Tae Young Ko[3)]

[1), 3)] Department of Energy and Resources Engineering, Kangwon National University, 1 Kangwondaehak-gil, Chuncheon-si, Gangwon-do, Republic of Korea
[2)] Jiyun E&C, Seoul, Republic of Korea
[3)] tyko@kangwon.ac.kr

ABSTRACT

Optimizing charging density in tunnel blasting significantly influences excavation efficiency, safety, and cost-effectiveness. Traditional blasting practices typically apply uniform charging densities across all blast holes, which fail to account for the distinct functional requirements of different blasting zones, leading to suboptimal excavation results and increased costs. To address this limitation, this study proposes a machine learning-based approach to predict optimal charging densities tailored specifically to the cut, stoping, lift, and contour zones in tunnel excavation. Blasting design data from Korean tunnel projects were analyzed using multiple machine learning algorithms, and their predictive performances were comparatively evaluated. SHAP analysis identified dominant parameters affecting each zone, including cut method for the cut zone, hole spacing for the stoping zone, round length for the lift zone, and rock type for the contour zone. The proposed models achieved R^2 values ranging from 0.78 to 0.97 across different zones, providing a reliable methodology for enhancing blasting efficiency, minimizing environmental impact, and reducing excavation costs.

1. INTRODUCTION

Tunnel blasting design plays a crucial role in determining excavation efficiency, safety, environmental impact, and project cost (Kwon 2024). A key parameter in this process is charging density (kg/m), which quantifies the amount of explosive per unit length of blast hole and is directly used in field charging design.

[1)] Graduate Student
[2)] CEO
[3)] Professor

According to Won (2006), uniform charging density was commonly applied to all blast holes in past tunnel blasting practices. However, recent approaches increasingly apply different charging densities tailored to each blasting zone (Zare 2006). Despite this shift, practical designs still rely on qualitatively defined ranges of charging density, limiting quantitative precision.

This study aims to develop more accurate and efficient blasting designs by applying machine learning techniques capable of modeling complex, nonlinear interactions among geological, geometric, and operational variables that traditional empirical methods cannot adequately capture. Specifically, we predict the charging density for each zone and identify key factors influencing the design through feature importance analysis. Since blasting zones differ significantly in their purpose and characteristics, they require distinct charging strategies. The cut zone creates the initial free face for subsequent blasting, the stope and lifter zones remove the bulk material, while the contour zone defines the final tunnel profile. (Min 2005; Hwang 2002).

The tunnel face was divided into four zones, namely cut, stope, lifter, and contour. Separate predictive models were developed for each, and SHAP (Shapley Additive Explanations) analysis was applied to identify key variables influencing charging density.

This approach supports charging strategies tailored to each zone, helping to improve blasting performance, reduce environmental impact, enhance construction quality, and lower costs.

2. DATA COLLECTION AND PREPROCESSING

This study utilized a comprehensive dataset of 208 tunnel blast rounds collected from 18 excavation sites across South Korea, representing diverse geological conditions including igneous, sedimentary, and metamorphic rock formations with varying strengths and structural characteristics.

Each entry includes 15 carefully selected input features that characterize the physical and operational conditions influencing blasting outcomes, based on established blasting theory and field engineering experience.

The input features are categorized into four groups based on their engineering significance. The input features are categorized into four groups based on their engineering significance. Geomechanical parameters characterize rock mass properties and include Rock Mass Rating (RMR) classified into five ordinal classes according to Bieniawski (1973), rock type (igneous, sedimentary, metamorphic), unit weight (kN/m^3), cohesion (MPa), internal friction angle (degrees), deformation modulus (GPa), and Poisson's ratio. Tunnel geometric parameters describe the excavation dimensions and include cross-sectional area (m^2) and round length (m), which directly influence blast volume and energy requirements. Blasting design parameters encompass minimum burden (mm), hole spacing (mm), and the number of charge holes per square meter of tunnel face (holes/m²), representing key operational variables that control explosive distribution and fragmentation efficiency.

Categorical variables include explosive type (emulsion, high-performance emulsion, or dynamite), cut blasting method, and controlled blasting method for the contour zone, which represent strategic choices affecting blasting performance and excavation quality.

These features represent key operational decisions affecting explosive distribution and confinement.

3. MACHINE LEARNING APPROACH

The dataset was divided into 80 percent for training and 20 percent for validation. Fivefold cross-validation was applied to the training set to ensure robustness and avoid overfitting. Numerical features were scaled to a range between zero and one using Min-Max normalization. Categorical variables, including rock type, explosive type, and blasting methods, were one-hot encoded for model compatibility.

Eleven algorithms were systematically evaluated, including linear models (multiple linear regression, Lasso, Ridge) for baseline comparison and advanced nonlinear models (support vector regression, K-nearest neighbors, decision tree, random forest, XGBoost, LightGBM, histogram-based gradient boosting, and artificial neural networks) to capture complex variable interactions.

Hyperparameters were optimized using GridSearchCV with predefined parameter grids, evaluated based on cross-validated R-squared scores to ensure robust model selection and prevent overfitting to the training data. Model performance was assessed using coefficient of determination, root mean squared error and mean absolute percentage error.

The best model for each blasting zone was retrained on the full training set and evaluated on the held-out validation set. SHAP analysis was performed to interpret feature contributions to charging density predictions.

4. RESULTS AND DISCUSSION

In this study, separate machine learning models were developed and evaluated for each blasting zone including cut, stoping, lift, and contour. A total of eleven regression algorithms were tested using five-fold cross-validation. Random Forest demonstrated the best performance in the cut zone ($R^2 = 0.97$), likely due to its ability to handle categorical variables such as cut method effectively, while XGBoost outperformed other models in the stope, lifter, and contour zones ($R^2 = 0.86$, 0.93, and 0.94, respectively), benefiting from its gradient boosting capability to model complex variable interactions.

Table 1 Cross-validation and final test results of machine learning models for predicting charging density in each blasting zone.

Category	**Cut Zone**	**Stoping Zone**	**Lift Zone**	**Contour Zone**
Best Model	RF	XGBoost	XGBoost	XGBoost
Train R^2	0.979	0.999	0.998	0.998
Train RMSE	0.018	0.002	0.002	0.002
Train MAPE	2.4	0.3	0.2	0.7
Test R^2	0.876	0.834	0.805	0.799
Test RMSE	0.043	0.031	0.060	0.023
Test MAPE	6.0	4.0	6.0	5.0
Final Test R^2	0.966	0.861	0.932	0.938
Final Test RMSE	0.021	0.041	0.036	0.009
Final Test MAPE	3.0	5.0	4.0	2.0

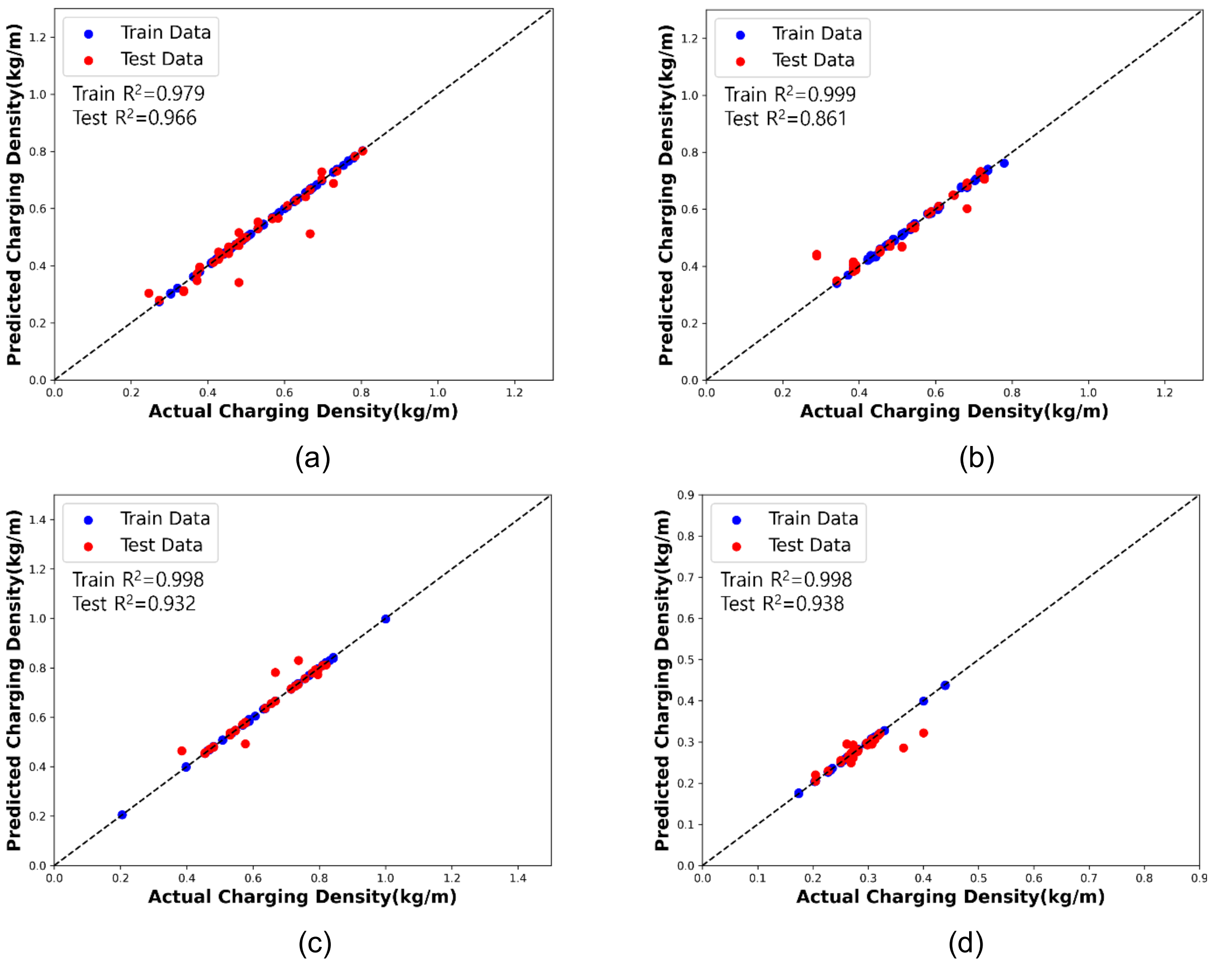

Fig. 1 Predicted vs. actual charging density for each blasting zone using the selected final model. (a) Cut zone; (b) Stoping zone; (c) Lift zone; (d) Contour zone.

Table 1 summarizes the cross-validation metrics and final test results for each zone-specific model. Fig. 1 shows the comparison between the predicted and actual charging densities for each blasting zone using the final selected models.

Fig. 2 shows the SHAP feature importance for each blasting zone. In the cut zone, Cut Method (SHAP value: 0.0619) emerged as the most influential factor, reflecting the critical role of cutting strategy in creating effective free faces, followed by Rock Type (0.0148), which determines the resistance to fracturing and energy requirements.

For both the stope and lifter zones, Round Length and Hole Spacing were dominant factors. In the stope zone, Round Length (0.0572) and Hole Spacing (0.0571) showed nearly equal importance, while in the lifter zone, Round Length (0.0947) was more influential than Hole Spacing (0.0313), indicating that advance length per round significantly affects charging requirements for bulk excavation.

In the contour zone, the most important features were Number of Charge Holes per Unit Area (0.01557) and Explosive Type (0.0085). These results indicate that each zone is influenced by distinct variables, emphasizing the need for zone-specific charging strategies.

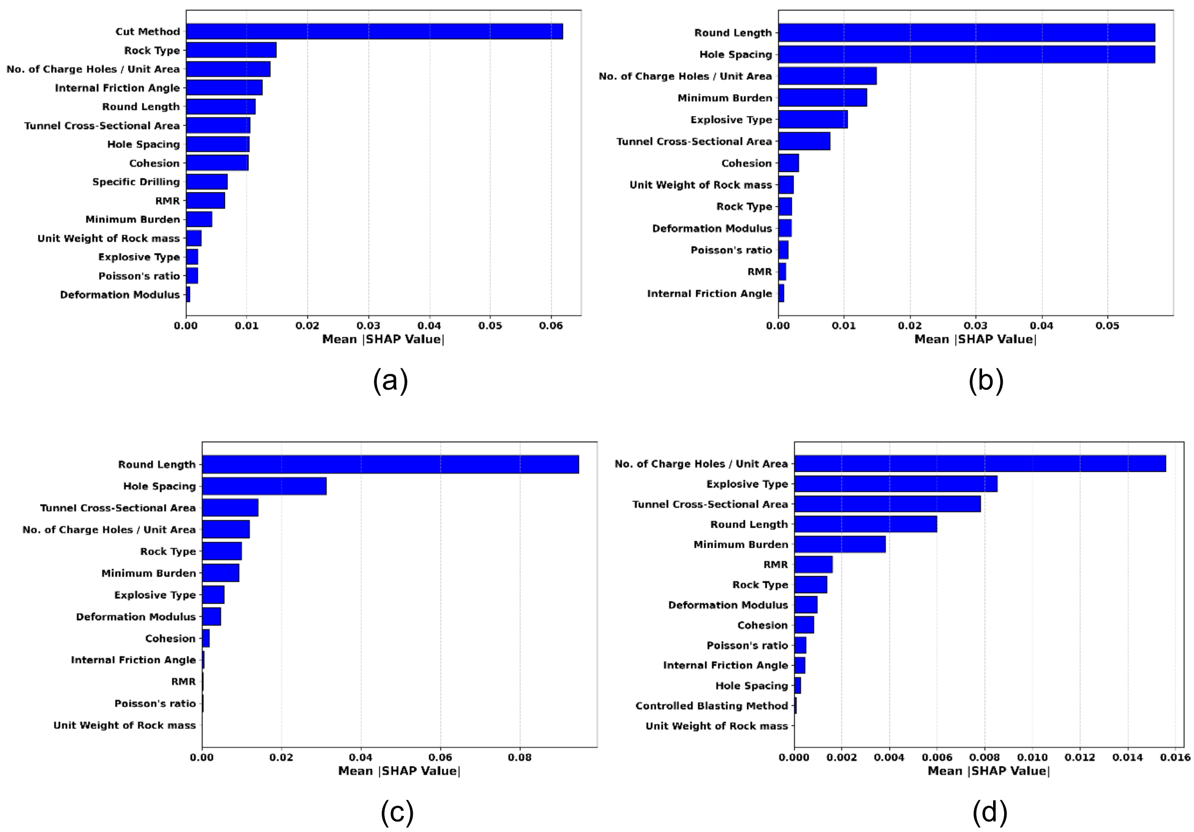

Fig. 2 SHAP feature importance analysis for each blasting zone. (a) Cut zone; (b) Stoping zone; (c) Lift zone; (d) Contour zone.

5. CONCLUSIONS

This study developed a machine learning-based approach to predict charging density in tunnel blasting, customized for the cut, stoping, lift, and contour zones. Based on data from 208 tunnel rounds in South Korea, eleven regression algorithms were evaluated. Random Forest showed the best performance for the cut zone, while XGBoost was optimal for the remaining zones.
SHAP analysis revealed distinct influential variables for each zone. Cut Method and Rock Type were most important in the cut zone; Round Length and Hole Spacing dominated in the stoping and lift zones; and the Number of Charge Holes per Unit Area and Explosive Type were key for the contour zone.
These results highlight the effectiveness of zone-specific machine learning models in improving charging design. However, the models are trained on Korean geological conditions and may require validation for application in different geological settings or tunnel construction methods.
The proposed framework offers a reliable, data-driven method to enhance blasting efficiency, control, and cost performance in tunnel excavation. Future work should focus on expanding the dataset to include international projects, incorporating real-time monitoring data, and developing adaptive models that can update predictions based on actual blasting performance feedback.

ACKNOWLEDGMENTS

This work was supported by a grant from the Korea Agency for Infrastructure Technology Advancement (KAIA), funded by the Ministry of Land, Infrastructure, and Transport (Grant RS-2024-00416524).

REFERENCES

Bieniawski, Z.T. (1973), "Engineering classification of jointed rock masses," *Trans. S. Afr. Inst. Civ. Eng.*, **15**, 335–344.

Hwang, H. and Lee, T.N. (2002), "A study on pilot test of the composition presplitting angle cut method in tunnel blasting," *J. Korean Tunn. Undergr. Space Assoc.*, **4**(4), 287–300.

Kwon, J.I., Lee, H.S. and Ko, T.Y. (2024), "Evaluation of machine learning techniques for predicting specific charge of cut hole blasting in tunnel," *J. Korean Soc. Rock Mech.*, **34**(6), 619–635.

Min, H.D., Jeong, M.S., Song, Y.S. and Park, Y.S. (2005), "Blast design methods considering site specific characteristics (II)," *J. Korean Tunn. Undergr. Space Assoc.*, **7**(4), 63–80.

Won, Y.H. and Im, H.U. (2006), “Study on the improvement of charging and initiation methods in tunnel excavation,” *Proc. KSEE Conf.*, Korean Soc. Explos. Blasting Eng., 105–124.

Zare, S. and Bruland, A. (2006), “Comparison of tunnel blast design models,” *Tunn. Undergr. Space Technol.*, **21**(5), 533–541.