Machine Learning-Based Sensitivity Analysis of Soil Ingredients and Soil Mechanical Properties on Tunnel Boring Machine (TBM) Advance Rate

Kayvan Mohammadi Atashgah[1,*] - Hamed Hashem Pour[2] - Mohammadreza Aref Azar[3]
[1] Department of Civil Engineering, Qazvin Branch, Islamic Azad University, Qazvin, Iran
Email: K_Mohammadi@alumni.iust.ac.ir, ORCID: 0000-0002-0136-328X (corresponding author)
[2] Department of Civil Engineering, The University of Texas at Arlington,
Email: hamed.hashempour@mavs.uta.edu
[3] Department of Civil Engineering, Iran University of Science and Technology
Email: engarefazar@yahoo.com

ABSTRACT

The prediction of Tunnel Boring Machine (TBM) advance rate is crucial for optimizing tunneling operations and ensuring cost-effective project management. This study investigates the use of machine learning (ML) models, specifically the Random Forest Regressor (RFR) and Support Vector Machines (SVM), to predict TBM performance in heterogeneous soil conditions. By leveraging data-driven approaches, the research provides insights into the factors influencing TBM advance rates, including soil composition, mechanical properties, and operational parameters. A comprehensive sensitivity analysis was performed to identify the key variables affecting TBM efficiency, focusing on soil properties such as cohesion, friction angle, and uniaxial compressive strength. The RFR and SVM were used as the primary ML models to predict the TBM advance rate based on these features. The models were trained on 80% of the dataset, while 20% was held back for testing and validation. Results indicate that these machine learning-based models, particularly the RFR and SVM, offer significant accuracy in predicting TBM performance, outperforming traditional empirical methods. The study contributes to the growing body of knowledge on ML applications in underground construction, with implications for enhancing TBM performance prediction, real-time monitoring, and reducing project risks.

Keywords: **Tunnel Boring Machine, TBM advance rate, machine learning, Support Vector Machines, soil properties, tunneling performance**

1. INTRODUCTION

Construction projects, especially large-scale underground projects such as metro systems, highways, and water tunnels, involve several complex factors that impact efficiency [1, 2]. Tunnel Boring Machines (TBMs) are crucial tools for these projects, but their performance is often influenced by varying geological conditions. These conditions affect the TBM's advance rate, which is critical for project timelines and costs [3, 4].

The performance of TBMs is significantly influenced by soil composition and its mechanical properties, including factors like clay, silt, sand, gravel, and rock fragments. The interaction between these soil ingredients and mechanical properties such as friction angle, plasticity index, cohesion, and unconfined compressive strength (UCS) determines the TBM's effectiveness. Machine learning (ML) models now offer a more efficient approach to analyzing these relationships compared to traditional empirical or physical testing methods [5, 6].

In this study, we used machine learning-based sensitivity analysis to investigate the effect of different soil ingredients and mechanical properties on TBM performance. By applying the Tornado Ranking Approach, we identified the most influential factors for TBM efficiency. This analysis helps engineers make informed decisions regarding soil treatment techniques and tunnel design, optimizing tunneling operations. Ultimately, our findings contribute to more cost-effective and timely underground construction projects by improving TBM performance in varying geological conditions.

2. LITERATURE REVIEW

2.1 Overview of TBM and Their Performance

TBMs are essential in modern underground construction, providing a mechanized means of excavating tunnels through a variety of geological conditions. The performance of a TBM is influenced by a range of factors, including the type of soil or rock it encounters, the machine's design, and operational parameters. The TBM advance rate (the rate at which the TBM progresses through the ground) is one of the most critical performance indicators in tunneling projects. A higher advance rate reduces project costs and timelines, whereas a lower advance rate can lead to significant delays and increased costs. Understanding the factors that impact the TBM advance rate is therefore fundamental to optimizing tunneling operations [7].

2.2 Soil Composition and Mechanical Properties

The soil encountered during tunneling plays a crucial role in determining the TBM’s performance. The composition of the soil, including the proportion of clay, silt, sand, gravel, and rock fragments, directly affects the cutting efficiency of the TBM. The granular nature of sand and gravel typically results in faster tunneling, whereas clay and silt can cause significant challenges for TBMs due to their cohesive and plastic nature. The mechanical properties of the soil, including friction angle, plasticity index, cohesion, and UCS, also influence the TBM advance rate. The friction angle is a measure of the internal resistance of the soil to shear deformation. Soils with a high friction angle, such as granular sands, offer less resistance to TBM cutting, leading to higher advance rates. On the other hand, cohesive soils with a low friction angle, such as clays, tend to generate higher cutting forces, slowing down the TBM. The plasticity index (PI), which measures the soil’s ability to deform without cracking, is particularly important for understanding the behavior of fine-grained soils, while cohesion and UCS are critical indicators of the soil's overall strength and ability to resist deformation during tunneling [7].

2.3 Traditional Methods for Assessing TBM Performance

Traditionally, the performance of TBMs has been evaluated through empirical methods, relying on historical data, physical tests, and engineering judgment. Several empirical models have been developed to estimate the TBM advance rate based on soil properties. For instance, The Terra-Machine Model uses a set of empirical equations to estimate the cutting force and the advance rate based on parameters such as soil strength and machine characteristics. These models often rely on simplified assumptions, such as uniform soil properties and ideal TBM performance, which may not always reflect real-world conditions [8].

Other studies have proposed the use of Rock Mass Rating (RMR) and Q-system classifications to evaluate rock mass properties and predict TBM performance. However, these methods have limitations when applied to heterogeneous soil conditions, where the properties can vary significantly across different layers of the tunnel. While these traditional methods provide useful initial estimates, they do not capture the complexity of the interaction between the TBM and varying geological conditions over time [9].

2.4 ML Approaches in TBM Performance Prediction

Advancements in ML and artificial intelligence (AI) have improved the accuracy of TBM performance predictions. ML models, such as regression models and decision trees, address the limitations of traditional approaches by capturing non-linear relationships between soil parameters, TBM settings, and advance rates. Support vector machines (SVM) and artificial neural networks (ANNs) have demonstrated superior accuracy in predicting TBM performance compared to traditional models, particularly when using diverse datasets of soil types and mechanical properties. These models excel at predicting TBM advance rates and offer reliable insights into performance [10].

However, the effectiveness of ML models depends on large, accurate datasets detailing soil properties, TBM specifications, and operational conditions. As more tunneling projects generate such data, ML methods are expected to play a critical role in real-time decision-making and predictive maintenance [10].

2.5 Sensitivity Analysis and Tornado Ranking Approach

Optimizing TBM performance requires understanding how soil and mechanical variations affect advance rates. Sensitivity analysis identifies key factors influencing performance and helps prioritize optimization efforts. The Tornado Ranking Approach, a tool for sensitivity analysis, ranks the importance of various parameters by analyzing how changes in each affect the TBM advance rate. The results, visualized in Tornado Diagrams, highlight the most critical factors. Soil properties like clay content, friction angle, and UCS are highly influential. Factors such as rock fragments and cohesion can slow operations, while sand and gravel improve advance rates. Combining ML with sensitivity analysis allows engineers to identify and optimize critical parameters, aiding in method selection and material treatment [11].

In summary, TBM performance depends on soil and mechanical properties. While traditional prediction methods struggle with complex geological conditions, ML enhances accuracy, and tools like the Tornado Ranking Approach offer valuable insights for optimization. These advancements significantly improve TBM efficiency, benefiting tunneling operations and the construction industry [11].

3. METHODOLOGY

Figure 1 shows that the current research was conducted in four steps, the methods of conducting them and their results will be discussed in detail in the following sections.

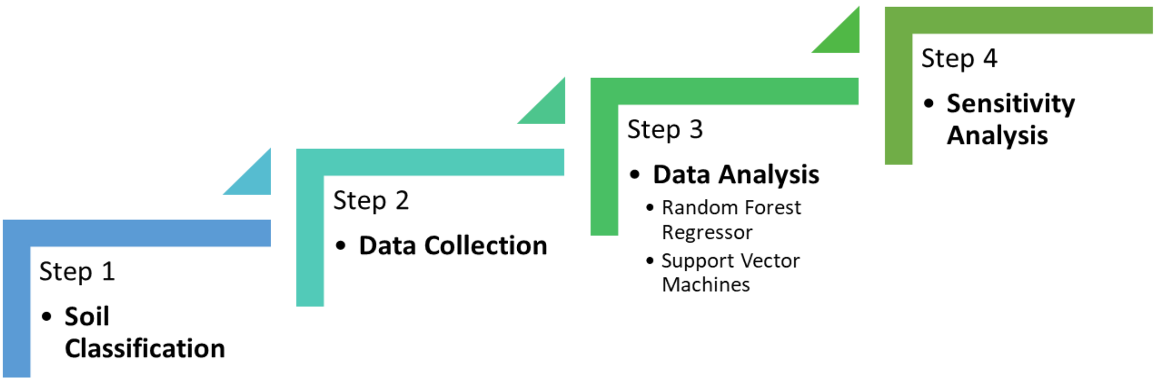

Fig. 1. *Steps to conduct the current study*

3.1 Soil Classification

The classification of the soil samples in this study was carried out using the ASHTO (American Association of State Highway and Transportation Officials) classification system, which is widely utilized for soil engineering in various infrastructure projects, particularly in tunneling. This system categorizes soils based on their grain size distribution and plasticity characteristics, with the main soil groups ranging from A-1 (granular soils) to A-7 (fine-grained, cohesive soils). The specific soil groups, such as A-2, A-3, A-4, and others, help identify the potential behavior of soil during tunneling and its impact on TBM performance. The grain size distribution and PI were determined for each soil sample using sieve analysis and hydrometer tests. This enabled a thorough classification of the soils, helping us understand their composition and the potential effects on TBM advance rates. The PI provides insight into the soil's ability to deform and influence the stability of tunneling operations, which is particularly important for understanding the cohesive behavior of fine-grained soils [12].

3.2 Data Collection

For this study, data was collected from a combination of field observations, geotechnical laboratory tests, and historical TBM performance records. A total of 50 tunneling projects were included, providing data on a variety of soil types and the corresponding TBM performance. The data collected included key soil components, such as the proportions of clay, silt, sand, gravel, and rock fragments, as well as important mechanical properties like friction angle, plasticity index, cohesion, and UCS. These mechanical properties were determined using triaxial tests, direct shear tests, and unconfined compression tests. Additionally, TBM advance rates (in meters per day) were recorded for each project, linking soil characteristics and mechanical parameters to the corresponding TBM performance. The comprehensive dataset collected was crucial for performing subsequent data analysis and developing insights into the influence of soil ingredients and mechanical properties on TBM performance.

3.3 Data Analysis

In this study, Random Forest Regressor (RFR) and SVM were applied to predict the TBM advance rate based on soil characteristics and mechanical properties. These models were trained using data from 50 tunneling projects, including key features such as soil composition (clay, silt, sand, gravel, rock fragments) and mechanical properties (friction angle, plasticity index, cohesion, unconfined compressive strength). The goal was to understand how these features influence TBM performance.

3.3.1 Random Forest Regressor (RFR)

RFR is an ensemble learning method that constructs multiple decision trees, each trained on a random subset of the data. The final prediction is made by averaging the predictions of all trees, which reduces overfitting. Mathematically, RFR minimizes the mean squared error (MSE) of the predictions [13]. Each tree makes a prediction, and the output of the forest is the mean of all individual tree predictions:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T}\hat{y}_t \qquad (1)$$

Where T is the number of trees and $\hat{y}_t$ is the prediction form the *t*-th tree.

3.3.1 Support Vector Machines (SVM)

SVM for regression aims to find a hyperplane that best fits the data by minimizing a loss function that includes both the error and a regularization term:

$$L(f(x), y) = \frac{1}{2}\,||w||^2 + C\sum_{i=1}^{n}\varepsilon_i \qquad (2)$$

Where *w* is the weight vector, ε_i are slack variables, and *C* controls the trade-off between margin size and error. The SVM uses an epsilon-insensitive loss function to tolerate small deviations between predicted and actual values, focusing on significant errors. Both models were trained on 80% of the dataset, with the remaining 20% used for testing, to predict TBM advance rate based on soil and mechanical features. Cross-validation techniques were used to ensure model robustness and to minimize the risk of overfitting, which is essential for making accurate predictions in real-world tunneling projects [10, 14]. RFR is an ensemble learning method that constructs multiple decision trees, each trained on a random subset of the data. The final prediction is made by averaging the predictions of all trees, which reduces overfitting. Mathematically, RFR minimizes the mean MSE of the predictions [13]. Each tree makes a prediction, and the output of the forest is the mean of all individual tree predictions:

3.4 Sensitivity Analysis

The final part of the methodology involved conducting a sensitivity analysis to understand how changes in soil composition and mechanical properties influence the TBM advance rate. This was done using the Tornado Ranking Approach, which systematically varies each parameter within a predefined range and measures its effect on TBM performance. Parameters such as clay content (ranging from 0% to 40%) and UCS (ranging from 200 kPa to 1000 kPa) were selected based on typical values observed in the dataset. Simulations were run for each parameter, where one factor was varied while others were kept constant. The results were analyzed to determine the sensitivity of the TBM advance rate to each parameter. A Tornado Diagram was created, ranking the parameters based on their effect on performance. This visual representation allowed us to identify which soil and mechanical features most significantly impacted TBM efficiency and provided actionable insights for optimizing tunnel design and machine operation [11].

4. RESULTS AND DISCUSSION

This study explores the relationship between various soil properties and the performance of TBMs, essential for underground excavation. The analysis relies on four key datasets, encompassing soil composition, mechanical properties, and the sensitivity of TBM performance to different ingredients and features. In this section, we provide a quantitative interpretation of the soil composition (Table 1) and TBM performance metrics (Table 2), followed by a qualitative discussion of the impact of soil ingredients (Table 3) and mechanical features (Table 4).

Table 1 details the soil composition for various soil categories, focusing on the proportions of clay, silt, sand, gravel, and rock fragments. This classification has important implications for the performance of TBMs. For example, Category A-1-a (Gravelly soils with little to no fines) has a high proportion of gravel (50-70%) and sand (25-40%), which means it consists primarily of coarse, granular materials. These types of soils are easier to tunnel through as they are less cohesive and present less resistance to TBM operations. Category A-3 (Fine sands with negligible fines) contains 85-95% sand and only 0-10% fines, indicating that the material is loose, with minimal cohesion. These soils are also relatively easy for TBMs to advance through, requiring less force for excavation and often leading to faster tunneling rates. Category A-6 (Clayey soils with low liquid limit) has a high clay content (35-50%) and lower sand (5-20%) and gravel (0-5%) content. Soils with high clay content exhibit higher cohesion and resistance to cutting, leading to slower TBM advancement. This type of soil can lead to significant operational difficulties and slower excavation rates.

***Table 1**. Soil Composition for Different Categories*

Category Name	Description	Clay (%)	Silt (%)	Sand (%)	Gravel (%)	Rock Fragments (%)
A-1-a	Gravelly soils with little to no fines.	0-5	0-10	25-40	50-70	0-10
A-1-b	Sandy soils with little to no fines.	0-5	0-10	60-85	10-30	0-5
A-2-4	Silty gravel and sand with low plasticity.	5-10	15-35	40-60	10-30	0-10
A-2-5	Silty gravel and sand with high liquid limit.	5-15	25-40	30-50	10-20	0-5
A-2-6	Clayey gravel and sand with low plasticity.	10-20	10-20	40-55	15-30	0-10
A-2-7	Clayey gravel and sand with high liquid limit.	20-35	15-25	25-40	10-20	0-5
A-3	Fine sands with negligible fines.	0-5	0-10	85-95	0-5	0-0
A-4	Silty soils with low liquid limit.	5-20	60-80	10-25	0-5	0-0
A-5	Silty soils with high liquid limit.	5-20	60-80	10-25	0-5	0-0
A-6	Clayey soils with low liquid limit.	35-50	20-40	5-20	0-5	0-0
A-7-5	Clayey soils with lower plasticity.	40-60	20-35	5-15	0-5	0-0
A-7-6	Clayey soils with higher plasticity.	50-70	20-30	5-15	0-5	0-0

Table 2 provides mechanical properties such as friction angle, plasticity index, cohesion, and UCS, which influence TBM performance. The impact on TBM advance rates is illustrated by the range of m/day values provided for each soil category.

Categories A-1-a and A-1-b both show a friction angle of 30-40° and a low PI (0-5), resulting in TBM advance rates between 50 and 200 m/day. These categories feature low cohesion and relatively easy excavation conditions, leading to higher operational efficiency.

Category A-6 (Clayey soils with low liquid limit) has a low friction angle (15-25°), high PI (40-60), and low cohesion (10-40 kPa), contributing to a relatively slow TBM advance rate of 30-45 m/day. The high clay content and plasticity increase resistance, making excavation more challenging.

Category A-3 (Fine sands with negligible fines) shows a high friction angle (35-45°) and low PI (0-5), resulting in a strong TBM performance with an advance rate of 60-180 m/day. The soil is primarily sand, which is less cohesive and offers minimal resistance to excavation.

***Table 2**. Soil Properties and TBM Performance*

Category Name	Friction Angle (°)	Plasticity Index (PI)	Cohesion (kPa)	UCS (kPa)	TBM Advance Rate (m/day)
A-1-a	30-40	0-5	10-20	300-500	60-200
A-1-b	30-40	0-5	10-20	300-500	50-180
A-2-4	25-35	5-15	20-50	200-400	5-130
A-2-5	25-35	15-25	20-60	250-500	50-120
A-2-6	20-30	15-30	30-80	300-600	40-100
A-2-7	20-30	25-40	40-100	350-700	40-60
A-3	35-45	0-5	10-30	400-700	60-180
A-4	20-30	30-50	5-20	100-200	40-60
A-5	20-30	30-50	5-20	100-200	35-45
A-6	15-25	40-60	10-40	50-150	30-45
A-7-5	15-25	40-60	10-40	50-150	20-35
A-7-6	10-20	50-70	10-30	30-100	10-25

Three groups of soil types are displayed in the figure 2 according to their TBM advance rate:

- **Fast Progress:** The fastest TBM advancement is possible with soil types classified as A-1 and A-3.
- **Moderate Progress:** A-2 soil types display a variety of moderate rates of development, with some subcategories advancing more quickly than others.
- **Slow Progress:** The slowest TBM advancement rates are found in soil types classified as A-4, A-5, A-6, and A-7.

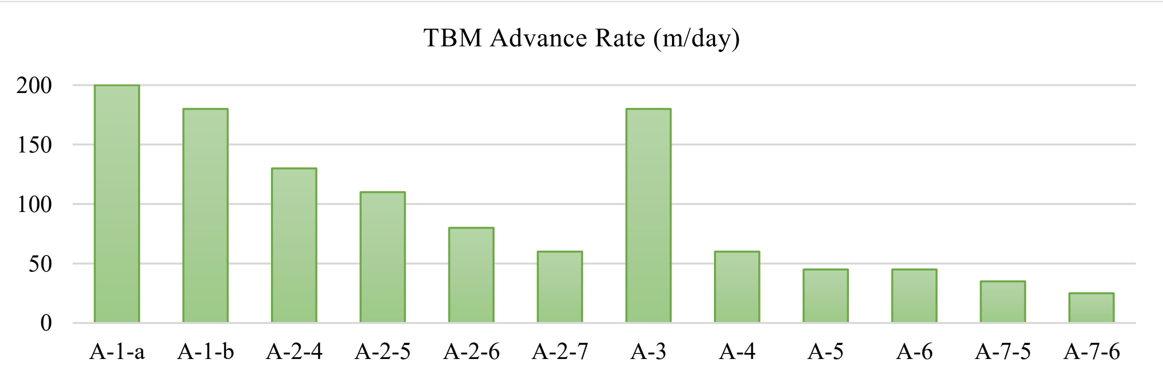

***Fig. 2.** TBM upper limit advance rate in different type of soil*

Tables 3 and 4 provide a sensitivity analysis of soil ingredients and mechanical features on the TBM advance rate, showing how different soil properties influence excavation speed. Table 3 highlights that sand has the most significant positive effect, greatly enhancing TBM progress by reducing resistance and facilitating smoother excavation. Gravel also contributes positively, though its impact is noticeably lower. On the other hand, silt and rock fragments negatively affect TBM performance, with silt causing a considerable decline and rock fragments further reducing excavation efficiency. However, clay has the most restrictive impact, significantly slowing down the TBM due to its high plasticity and cohesive nature. This confirms that soils rich in clay present major excavation challenges.

***Table 3**. Sensitivity Analysis of Soil Ingredients*

Ingredient	Impact on TBM Advance Rate (m/day)	Peak sensitivity
Sand (%)	The most increasing factor	+20
Gravel (%)	increase	+4
Rock Fragments (%)	decrease	-3
Silt (%)	decrease	-15
Clay (%)	The most decreasing factor	-35

Table 4 examines mechanical properties and their role in TBM performance. The friction angle is the only feature that improves TBM progress, as higher values enhance soil stability and reduce machine resistance. In contrast, plasticity index has the strongest negative effect, indicating that highly plastic soils create major delays and demand greater excavation effort. Cohesion and UCS also contribute to a decline in TBM speed, though their influence is less dominant. These findings emphasize that soils with high plasticity and cohesion pose greater resistance, while softer, less cohesive materials allow for smoother excavation.

***Table 4**. Sensitivity Analysis of Soil Mechanical Features*

Mechanical Feature	Impact on TBM Advance Rate (m/day)	Peak sensitivity
Friction Angle	increase	+18
Cohesion (kPa)	decrease	-3
UCS (kPa)	decrease	-7
Plasticity Index	The most decreasing factor	-30

5. VALIDATION

The results of this study align with existing research, reinforcing the well-established relationship between soil properties and TBM performance. Sand remains the most influential factor in improving excavation efficiency, as it reduces cohesion and allows the machine to advance with minimal resistance. These findings closely match previous studies, which also highlight sand as a key element in optimizing TBM performance. Similarly, gravel enhances tunneling efficiency, though to a lesser extent than sand, a pattern that is consistent with research on gravel-rich soils [15].

In contrast, clay and rock fragments present significant obstacles to TBM progress, with clay being particularly problematic. High clay content greatly reduces excavation efficiency, while rock fragments further impede progress by increasing resistance. These findings are in line with previous studies, which emphasize the negative impact of clay-rich and rocky soils on tunneling operations [16].

Additionally, the friction angle plays a crucial role in improving TBM performance, reinforcing past research that highlights its importance in stabilizing soil and reducing excavation resistance [16].

Overall, these findings validate the results of this study through comparison with previous academic research, confirming established trends in soil mechanics and TBM performance.

6. CONCLUSION

This study demonstrates the crucial role that soil composition and mechanical properties play in determining the performance of TBMs. Soils rich in clay and silt lead to slower advance rates due to increased cohesion and friction, whereas soils with high sand and gravel content provide better conditions for rapid tunneling. The sensitivity analysis further reveals that rock fragments and mechanical features such as friction angle, plasticity, cohesion, and UCS also significantly influence TBM efficiency. The validation of these findings against existing research confirms the robustness of our results and highlights the importance of considering these factors when planning tunneling operations. This information is valuable for engineers and decision-makers to optimize tunneling strategies and improve overall efficiency in underground construction projects.

REFERENCES

[1] Hasehmpour, H., K. Mohammadi Atashgah, and M. Karbalaei Rezaei, *An investigation into the role of nano-silica in improving strength of lightweight concrete.* European Online Journal of Natural and Social Sciences, 2014. **3**(4): p. pp. 1058-1067.

[2] Ghousi, R., M. Khanzadi, and K. Mohammadi Atashgah, *A flexible method of building construction safety risk assessment and investigating financial aspects of safety program.* International Journal of Optimization in Civil Engineering, 2018. **8**(3): p. 433-452.

[3] Mohammadi Atashgah, K., et al., *Developing a model for time-cost trade-off optimization problem considering overdraft issue in uncertain environments.* Journal of Industrial and Systems Engineering, 2022. **14**(3): p. 259-279.

[4] Atashgah, K.M., et al., *A Development Model for Identifying the Uncertainty Sources and Their Impacts on Bridge Construction Projects.* The Baltic Journal of Road and Bridge Engineering, 2023. **18**(1): p. 140-166.

[5] Pour, H.H., *Study of Parameters impacting productivity of tunnel boring machines*. 2017, University of Texas at Arlington.

[6] Atashgah, K.M., *The impact of materials cost on the weight of concrete buildings.*

[7] Zhang, Y., et al., *A Visual Survey of Tunnel Boring Machine (TBM) Performance in Tunneling Excavation: Mainstream Direction, Brief Review and Future Prospects.* Applied Sciences, 2024. **14**(11): p. 4512.

[8] Afradi, A., A. Ebrahimabadi, and T. Hallajian, *Prediction of the number of consumed disc cutters of tunnel boring machine using intelligent methods.* Mining of Mineral Deposits, 2021.

[9] Palmstrom, A. and E. Broch, *Use and misuse of rock mass classification systems with particular reference to the Q-system.* Tunnelling and underground space technology, 2006. **21**(6): p. 575-593.

[10] Zhou, J., et al., *Optimization of support vector machine through the use of metaheuristic algorithms in forecasting TBM advance rate.* Engineering Applications of Artificial Intelligence, 2021. **97**: p. 104015.

[11] Fatemi, S.A., M. Ahmadi, and J. Rostami, *Evaluation of TBM performance prediction models and sensitivity analysis of input parameters.* Bulletin of Engineering Geology and the Environment, 2018. **77**: p. 501-513.

[12] Alade, S.M., *Correlation of unified and AASHTO soil classification systems for soils classification.* Journal of Earth Sciences and Geotechnical Engineering, 2018. **8**(1): p. 39-50.

[13] Segal, M.R., *Machine learning benchmarks and random forest regression.* 2004.

[14] Fili, R., F. Bagherpoor, and K. Mohammadi Atashgah, *Developing a new fuzzy inference model for warehouse maintenance scheduling under an agile environment.* International Journal of Nonlinear Analysis and Applications, 2024. **16**(1): p. 297-306.

[15] Ansari, T., et al., *Investigating Effect of Soil Grading Parameters on Tool Wear in Mechanized Tunneling using EPB-TBM Machine.* Journal of Mining and Environment, 2024. **15**(1): p. 301-321.

[16] Barzegari, G., A. Uromeihy, and J. Zhao, *Parametric study of soil abrasivity for predicting wear issue in TBM tunneling projects.* Tunnelling and underground space technology, 2015. **48**: p. 43-57.