JOURNAL OF ROCK MECHANICS
VOL. 9, NO. 1, PP. 47-60.
https://doi.org/10.22034/IRSRM.2025.540267.1054

The Estimation of TBM Penetration Rate using Artificial Neural Network Optimized with Particle Swarm Optimization and Firefly Algorithms, Case Study: Tabriz Metro Line 2

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Received: 14 April 2025 Accepted: 21 June 2025
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Keywords

Artificial Neural Network (ANN)
Firefly Algorithm (FA)
Particle Swarm Optimization (PSO)
EPB TBM
Penetration Rate Prediction
Tabriz Metro
Soil Mechanics Parameters

Abstract

The penetration rate (PR) is a critical parameter in tunnelling, as it directly determines project timelines, cost, and overall efficiency. Developing accurate predictive models for the penetration rate (PR) is crucial for optimizing tunnelling performance and enabling more effective project planning. To meet this need, this study employs advanced metaheuristic optimization algorithms to augment an artificial neural network (ANN) for improved penetration rate (PR) prediction. Specifically, particle swarm optimization (PSO) and the firefly algorithm (FA) were employed to refine the model's accuracy. The research utilized data from the Tabriz Metro Line 2 project. The data integrated key influencing factors, which were categorized as follows: geological parameters, including soil friction angle, cohesion, unit weight, shear modulus, and water table depth; and machine parameters, including torque, thrust force, and rotational speed. The explicit goal of the model's optimization was to minimize the normalized mean squared error (NMSE) for its predictions against the actual measured values. The results demonstrate that both PSO and FA significantly enhanced the predictive performance of the baseline ANN model. However, the firefly algorithm proved superior, achieving a higher coefficient of determination (R^2 = 0.836 for test data, compared to 0.780 for the PSO-optimized model) and a lower NMSE. This key outcome is attributed to the FA's robust search capabilities, confirming its effectiveness in identifying optimal model parameters for complex, nonlinear relationships in tunnelling. The findings provide a reliable, data-driven framework for predicting TBM performance, offering substantial practical value for project planning and execution in geotechnical engineering.

I. INTRODUCTION

Tunnelling in urban areas involves specific challenges due to the sensitivity of these regions. Earth pressure balance (EPB) tunnel boring machines (TBMs) have seen a marked increase in deployment, a trend most evident in urban infrastructure projects. One approach to predict the efficiency of these machines is to estimate their penetration rate, which is the ratio of the distance excavated to the time taken during continuous excavation. This rate represents the machine's instantaneous advance rate. It is typically measured in millimeters per revolution (mm/rev) of the cutterhead or in meters per hour (m/h). Generally, a higher advance rate results in a shorter project execution time. Assessing and forecasting TBM performance, along with the factors affecting it, aims to improve accuracy, speed, and risk reduction. The first step involves identifying the parameters influencing machine performance, such as geological conditions, TBM operational parameters, and route engineering. Data from previous excavations and geological studies are used to collect all relevant factors, enabling the development of a precise model for predicting machine penetration rates.

Given the critical role of predicting the penetration rate in tunneling operations, researchers have long sought effective methods to estimate it, resulting in numerous theoretical and empirical approaches. Benardos. (2008) applied neural network modeling to analyze TBM performance [2]. In this study, due to the significant impact and complexity of geological conditions, machine parameters such as thrust force and torque were excluded. The input parameters included the rock quality designation (RQD), rock weathering degree, rock mass rating (RMR), uniaxial compressive strength, overburden depth, groundwater conditions (water table depth), and rock permeability. Bazargan et al. (2022) investigated the performance of cutting tools (disc cutters and rippers) in silty-sand soils via artificial neural networks (ANNs), and their results revealed that rippers outperform disc cutters in silty soils, as shown by the ANN model [3]. Darbor et al. (2020) demonstrated that a neuro-fuzzy (ANFIS) model achieves superior accuracy in predicting the EPB TBM penetration rate for the Tabriz Metro Line 2 project, with sensitivity analysis confirming cutter head torque as the most influential parameter[4]. Nickjou Tabrizi et al. (2022), using a simulator, determined that wear increases with higher rotational speed and operation time but decreases with a greater penetration rate; they also found that maximum abrasivity occurs at 7% soil moisture [5]. Khodaee Ashestani et al. (2023) employed neural networks to accurately predict TBM penetration rates in Tabriz Metro, identifying soil cohesion and friction angle as the most influential geotechnical parameters[6]. Khoshzaher et al. (2023) investigated the effects of fine-grained soil content and moisture on TBM clogging and tool wear, finding that increased fines and moisture significantly elevate clogging and wear, while foam injection effectively mitigates these issues [7]. Darbor et al. (2023) linked wear to soil properties, demonstrating that maximum abrasion occurs at 10% fine grain content—a point that aligns with the Talbot curve for maximum density—and that increased soil density significantly elevates wear rates [8]. Ansari et al. (2024) Further exploring soil abrasiveness, established the sorting coefficient as a key evaluation criterion. They reported that tool wear increases with parameters like D_{10}, D_{30}, and D_{60} in soils containing more than 10% fines, but decreases in soils with less than 10% fines [9]. Amoun & Chakeri. (2024) demonstrated that soil conditioning with foam can reduce cutting tool wear by 58% and cutterhead torque by 34% in EPB-TBM tunneling, with wear behavior critically dependent on fines content and grading parameters [10]. Maleki et al. (2025) utilized a novel small-scale Linear Cutting Machine (LCM) to show that disc cutter wear increases with penetration depth across all rock types, is most severe in basalt, and correlates most strongly with Brazilian Tensile Strength [11]. Chakeri et al. (2024) experimentally and numerically analyzed disc cutter wear across eight rock types using a novel laboratory TBM simulator and PFC3D software, finding good agreement between the physical and simulated models particularly for rock abrasion [12]. Chakeri et al. (2025) developed a novel small-scale linear cutting machine (LCM) and used finite element method (FEM) simulations to evaluate disc cutter performance across nine rock types, finding that specific energy was highest in porous Basalt-1 and lowest in soft Travertine-1, while wear was most severe in fine-grained Fossiliferous Limestone [13]. Yagiz et al. (2009) employed multivariate nonlinear regression and neural networks to estimate the penetration rate using parameters such as uniaxial compressive strength, brittleness index, joint spacing, and the angle between joints and the tunnel axis [14]. Gholamnejad & Tayarani. (2010) used artificial neural networks to predict the penetration rate via parameters such as the uniaxial compressive strength, joint spacing, and RQD [15]. Yagiz & Karahan. (2011) used the particle swarm optimization algorithm to optimize the coefficients of a nonlinear equation that defines the penetration rate based on independent variables including uniaxial compressive strength, brittleness index, joint spacing, and the angle between joints and the tunnel axis [16]. Torabi et al. (2013) examined the impact of geotechnical parameters on TBM performance in the Tehran–Shomal highway project, revealing that the uniaxial compressive strength (UCS) most significantly affects the penetration rate whereas utilization is largely influenced by management-related factors [17]. The superior reliability of artificial neural networks (ANNs) over statistical methods for predicting performance emphasizes the need for effective management to minimize downtime and optimize TBM efficiency. Salimi et al. (2016) predicted TBM performance in hard rock using nonlinear regression analysis and artificial intelligence algorithms, which incorporated parameters such as uniaxial compressive strength (UCS), rock quality designation (RQD), and Brazilian tensile strength (BTS) [18]. Gao et al. (2015) predicted the TBM penetration rate via support vector regression (SVR) [19]. Jamshidi. (2018) developed statistical models to predict tunnel boring machine (TBM) penetration rates via brittleness indices derived from rock properties [20]. The results demonstrate that multiple regression models provide high accuracy and reliability, which makes them valuable tools for the planning and cost control phases of tunneling projects. Fatemi et al. (2018) conducted a sensitivity analysis on input parameters with various TBM performance prediction models [21].

Materials and methods

A. *Study Area*

Line 2 of the Tabriz Metro is a vital component of the Tabriz urban rail network, spanning approximately 22.4 kilometers and comprising 22 stations. The route connects key areas across the city, starting from the western part of Tabriz and extending to the eastern regions, ultimately terminating at the Tabriz International Exhibition. The tunnel for Line 2 features an external diameter of 9.49 m, an internal diameter of 8.48 m, a segment thickness of 35 cm, and an injection zone thickness of 15.5 cm. The tunnel depth varies between 15 and 28 m along the route, reflecting the diverse geological conditions of the area. Excavation

Fig. 1. The EPB-type tunnel boring machine in the Tabriz Metro Line 2 project.[1]

employs an earth pressure balance (EPB) tunnel boring machine (TBM), a technology well-suited to the mixed soil and rock conditions encountered in the region. Figure 1 illustrates the TBM used for the excavation of Line 2, highlighting the advanced engineering techniques employed in this project.

This metro line is expected to significantly enhance urban mobility, reduce traffic congestion, and contribute to the sustainable development of Tabriz by providing a reliable and efficient public transportation system. The project also addresses the challenges posed by the city's complex geology, ensuring safe and efficient tunneling operations. In this section, geotechnical parameters for designing various soil and rock layers along the route are determined basis of observations during borehole drilling, field and laboratory test results, geotechnical studies of nearby projects, and engineering judgment. The geotechnical parameters were proposed by analyzing laboratory and field test results, considering geotechnical studies of projects near the design boundary, and applying engineering judgment. The statistical values of the studied data were also determined. The input parameters for the predictive model were selected based on the specific ground conditions encountered in the Tabriz Metro Line 2 project and the operational principles of the EPB TBM. While the route featured mixed soil and rock conditions, the geological environment was predominantly soil-like, comprising cohesive soils, weathered rock, and sheared formations. In such materials, the behavior of the excavated mass is governed primarily by soil mechanics principles. Consequently, geotechnical parameters fundamental to soil shear strength and deformation—such as internal friction angle, cohesion, unit weight, and shear modulus—were deemed most relevant for predicting TBM penetration rate. Traditional rock mass classification parameters (e.g., Uniaxial Compressive Strength (UCS), Rock Quality Designation (RQD)), while crucial in hard rock tunneling, were not considered as they are not representative of the bulk material behavior controlling EPB TBM performance in these specific ground conditions.

The dataset for machine parameters was collected from drilling data between Stations 1 and 3. **Figure 2** shows the geological profile of the studied route between these stations. Geotechnical data were obtained from laboratory tests or in situ tests. For both algorithms used in this study to optimize the penetration rate, eight input variables were used, including torque (MN-m), thrust force (KN), speed (mm/min), internal friction angle (°), cohesion (kPa), specific weight (gr/m³), and water table level (m). The sole output in this study was the penetration rate (mm/rev). Table 1 presents the maximum, minimum, mean, standard deviation, and variance values for each parameter.

TABLE 1- DESCRIPTIVE STATISTICS

Parameter	*Minimum*	*Maximum*	*Mean*	*Standard Deviation*	*Variance*
Torque (MN·m)	1.10	5.30	4.1347	0.3474	0.121
Thrust Force (kN)	7195.00	36265.00	22371.02	4734.80	22418313.64
Speed (mm/min)	5.00	55.00	33.30	4.77	22.80
Internal Friction Angle (°)	5.04	28.48	15.59	5.81	33.71
Cohesion (kPa)	11.19	58.93	41.36	11.39	129.70
Specific Weight (gr/m³)	1.82	1.97	1.90	0.05	0.002
Shear Modulus (kg/cm²)	28.52	155.20	71.43	27.59	761.16
Water Table Level (m)	11.00	17.80	14.67	1.96	3.82

Penetration Rate (mm/rev)	4.00	36.00	19.10	3.66	13.38

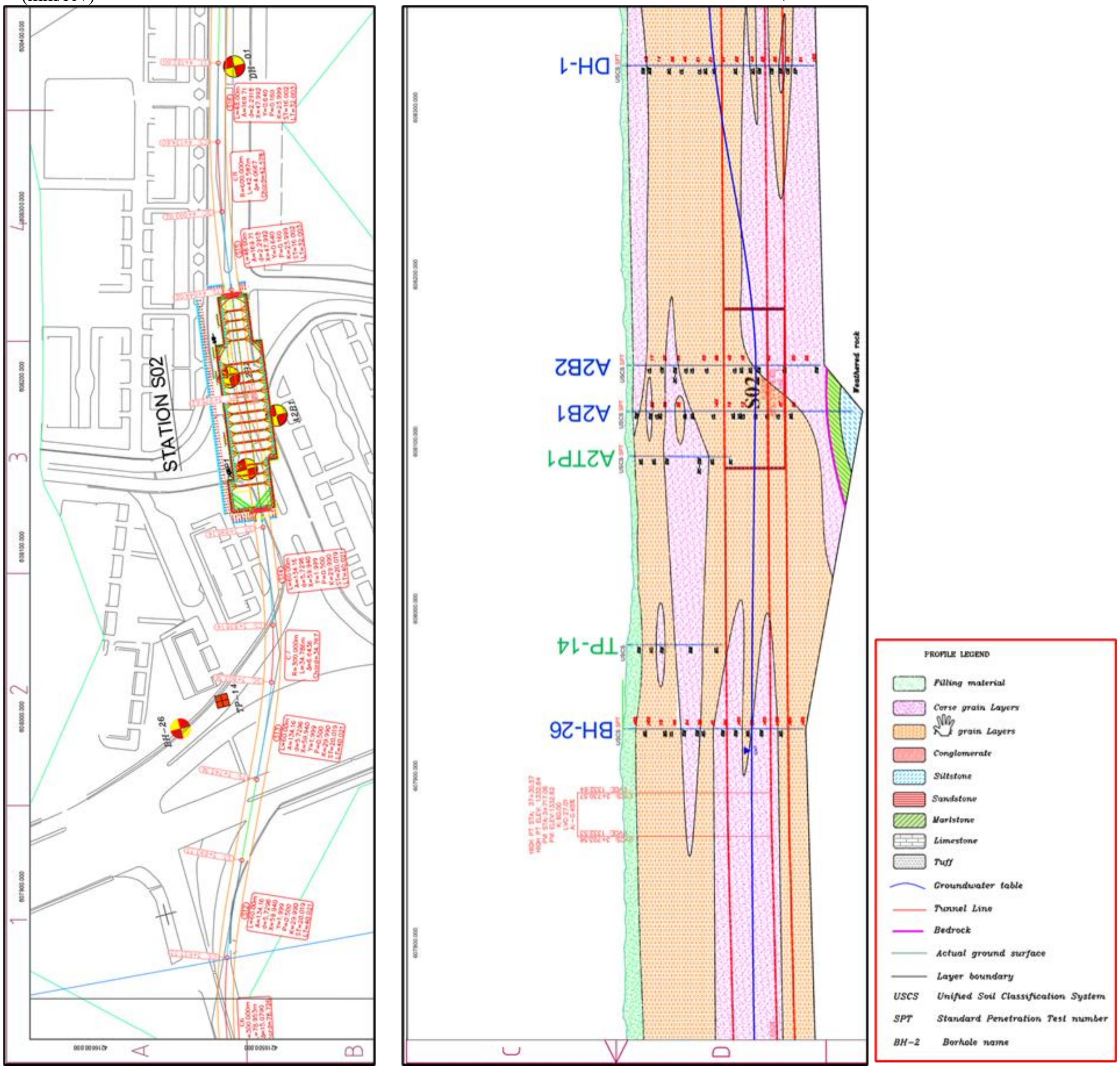


Fig. 2. Soil profile station 01(X:607266, Y:4216548).

B. Hybrid ANN-FA Model

The firefly algorithm (FA) was introduced by Yang. (2009) [22]. It is one of the latest swarm intelligence-based optimization algorithms. The FA shares some similarities with the PSO and BFO algorithms, and with proper parameter selection, its performance can closely resemble that of the standard PSO algorithm. According to Sayadi et al. (2010), although the Firefly Algorithm (FA) was initially applied to unconstrained continuous optimization problems, recent research has focused on extending it to combinatorial optimization problems [23].

*1) **Utilizing the Firefly Algorithm to Solve Unconstrained Continuous Optimization Problems***

1) Initialization of Parameters: Assign appropriate values to the parameters, where:
2) γ: Light absorption coefficient of the environment, $MaxGeneration$: Maximum number of iterations (termination condition for the algorithm), $\beta_{\circ}$: Maximum attractiveness between two fireflies, α: Random movement coefficient, m: Number of fireflies, t: Iteration counter.
3) Initialization of Fireflies: Generate an initial population of fireflies (i.e., a set of vectors $(i = 1,2,\ldots,m)$ x_i randomly within the problem domain).
4) Light intensity calculation: Determine the light intensity of $i-$th firefly (I_i) using the objective function value at that point, $f(x_i)$.
5) Termination Check: If $t < Max\ Generation$, proceed to step 5; otherwise, go to step 11.
6) Iterate Over Fireflies: For $i = 1{:}\,m,$ perform steps 6 and 7.

7) Movement of Fireflies: If $I_j > I_i$, move the i-th firefly toward the j-th firefly. The position of the i-th firefly is updated via Equation 9:

$$x_i \leftarrow x_i + \beta_\circ e^{-\gamma r_{ij}^2} + \alpha\left(rand - \frac{1}{2}\right) \quad (9)$$

8) where r_{ij} is the Euclidean distance between the two fireflies. After the position is updated, the light intensity of the i-th firefly is updated.
9) 8. Randomize Best Firefly: The position of the best (i.e., optimal) firefly is randomly adjusted.
10) 9. Sort Fireflies: The fireflies are sorted based on the obtained cost function values, and the best solution is identified.
11) 10. Repeat: The process returns to step 4.
12) 11. Output Best Solution: The optimal solution to the problem is the best solution found across all iterations.

In step 7, equation (9) is applied to guide a less bright firefly toward a brighter firefly. In a more general form, this equation can be expressed as:

$$x_i \leftarrow x_i + \beta(x_j - x_i) + \alpha\left(rand - \frac{1}{2}\right) \quad (10)$$

Where β is the attractiveness coefficient. Note that in equations (1) and (2), r_{ij} is the distance between the (i)-th and (j)-th fireflies, defined as:

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{n}\left(x_{i,k} - x_{j,k}\right)^2} \quad (11)$$

Here, $x_{i,k}$ is the (k)-th component of the position vector (x_i) for the (i)-th firefly. In equation (9), the term $\beta_\circ e^{-\gamma r_{ij}^2}$ ensures that the light intensity received by the (i)-th firefly from the (j)-th firefly decreases with increasing distance, reducing the attraction between them. In a lossless environment, the second term on the right-hand side of equation (9) should be substituted with:

$$\beta = \frac{\beta_\circ}{r_{ij}^2} \quad (12)$$

In an environment with a constant absorption coefficient γ, the light intensity at a distance r from the source is expressed as $I(r) = I_\circ e^{-\gamma r}$, where $I_\circ$ represents the light intensity at the source. Thus, equation (9) combines the inverse square law and the light absorption law to determine the attraction between fireflies. Theoretically, any decreasing function of distance can be used to define attractiveness. For example, if Łukasik & Żak. (2009), the second term in equation (9) is written as [24]:

$$\beta = \beta_\circ e^{-\gamma r_{ij}^2} \quad (13)$$

In reference [10], a less aggressive attractiveness coefficient is suggested:

$$\beta = \frac{\beta_0}{1 + \gamma r_{ij}^2} \quad (14)$$

Since in equations (9), (13), and (14), β reduces to β_0 when $r_{ij} = 0$, β_0 is called the maximum attractiveness.

A key characteristic of the firefly algorithm is its nested loop structure, which leads to a computational complexity of $O(m^2)$, meaning the processing time scales with the square of the population size (number of fireflies). Consequently, while increasing the number of fireflies enhances the likelihood of locating the global optimum, it also significantly increases computational demands and may reduce the algorithm's efficiency.

2) Selecting Appropriate Parameter Values in the Firefly Algorithm

In the firefly algorithm, the interaction between fireflies is determined by the attractiveness coefficient β, which depends on two key parameters: the maximum attractiveness β_0 and the absorption coefficient γ. The parameter β_0 represents the attractiveness between fireflies when they are at the exact location, typically chosen between 0 and 1. When $\beta_0 = 0$, the algorithm behavior as a random search without memory, with fireflies operating independently. Conversely, when $\beta_0 = 1$, the brightest firefly attracts others with full strength, particularly those in its vicinity. Empirical studies suggest that $\beta_0 = 1$ often yields optimal results.

The parameter γ controls how the attractiveness between fireflies diminishes as the distance increases. When $\gamma = 0$, attractiveness remains constant regardless of distance, which deviates from the natural behavior of fireflies. As $\gamma \to \infty$, the attractiveness β approaches zero, which causes the algorithm to degrade into a purely random search and lose its collective, firefly-driven behavior. Yang. (2010) recommends $\gamma \in [0,10]$, and Łukasik & Żak. (2009) provide further recommendations for its application [25], [24].

$$\gamma = \frac{\gamma_0}{r_{max}} \quad (15)$$

Or

$$\gamma = \frac{\gamma_0}{r_{max}^2} \quad (16)$$

where $\gamma_0 \in [0,10]$

$$r_{ij} = \|x_i - x_j\|, \quad \forall x_i, x_j \in S \tag{17}$$

S represents the collection of all points within the domain of the optimization problem.

The final parameter in equation (1) is α. Typically, αα is selected from the range [0, 1]. Importantly, when $\alpha = 1$, all the variables in the optimization problem are randomly shifted by ± 0.5 from their nominal values.

C. Hybrid ANN–PSO Model

The hybrid ANN-PSO model integrates the complementary strengths of artificial neural networks (ANNs) for predictive modeling and particle swarm optimization (PSO) for efficient search, thereby enhancing both predictive accuracy and optimization performance. Artificial neural networks (ANNs) are particularly adept at modeling complex, nonlinear systems due to their inherent adaptive learning capabilities. Conversely, particle swarm optimization (PSO) is a robust metaheuristic algorithm, inspired by the collective behavior of bird flocks or fish schools, which excels at efficiently navigating complex, high-dimensional search spaces to identify near-optimal solutions without requiring gradient information Particle swarm optimization (PSO), introduced byKennedy & Eberhart. (1995), is a nature-inspired metaheuristic designed to solve numerical problems with large search spaces without requiring gradient information [26]. It has been effectively applied in various domains, including neural network training, power distribution optimization, and process identification. While PSO is primarily used for continuous optimization, ongoing research aims to extend its application to combinatorial problems.

1) Rules Governing Animal Swarm Behavior in Nature

Three fundamental rules describe the collective movement of animal swarms:

Separation: Avoid crowding nearby members of the group.

Alignment: Steer towards the average heading (direction and velocity) of nearby members.

Cohesion: Staying close to other members of the group.

2) Utilize the PSO Algorithm to Solve Unconstrained Continuous Optimization Problems

Initialization: Set up a population of particles by assigning random positions and velocities within a DD-dimensional search space.

Evaluation: Determine the fitness of every particle in the population to evaluate its effectiveness in solving the problem.

Update: Determine the velocity of each particle via equation (18) and update their positions via equation (19). (Kennedy & Eberhart. (1995), Shi & Eberhart. (1998)) [26], [27]

Termination: End the algorithm if the termination criterion is met; otherwise, return to step 2.

Where:

$V_j(i)$ represents the velocity of particle j during iteration i.

$X_j(i)$: Denotes the position of particle j at iteration i.

$P_{best,j}$: Best position of particle j thus far.

G_{best}: Indicates the best position discovered by the entire swarm.

$\theta(i)$: Inertia weight at iteration i.

c_1, c_2: Acceleration coefficients.

r_1, r_2: Random numbers generated between 0 and 1.

$\theta_{max}, \theta_{min}$: Maximum and minimum values of the inertia weight.

i_{max}: Maximum number of iterations.

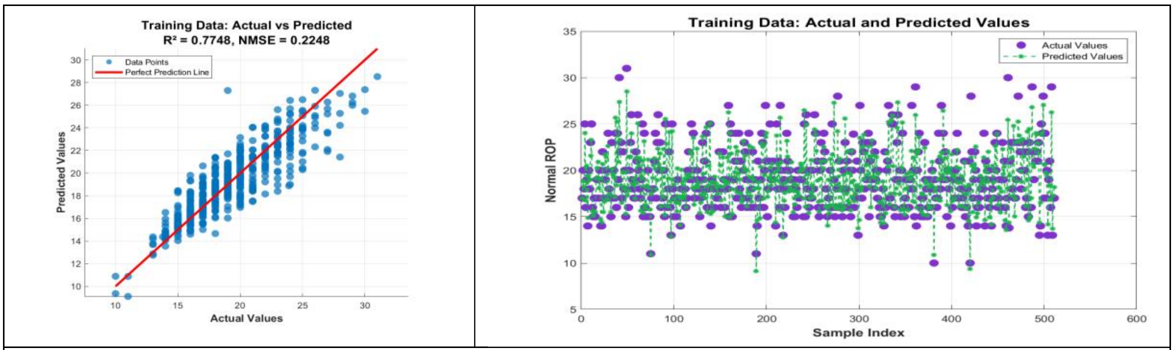
Xinchao. (2010) and Zhan et al. (2009) mentioned that, in most cases, the values $\theta_{max} = 0.9$ and $\theta_{min} = 0.4$ are used for this purpose [28], [29]. These values, which have been obtained empirically through extensive and diverse simulations, yield satisfactory results in most problems.

D. Fitness Function and Error Values

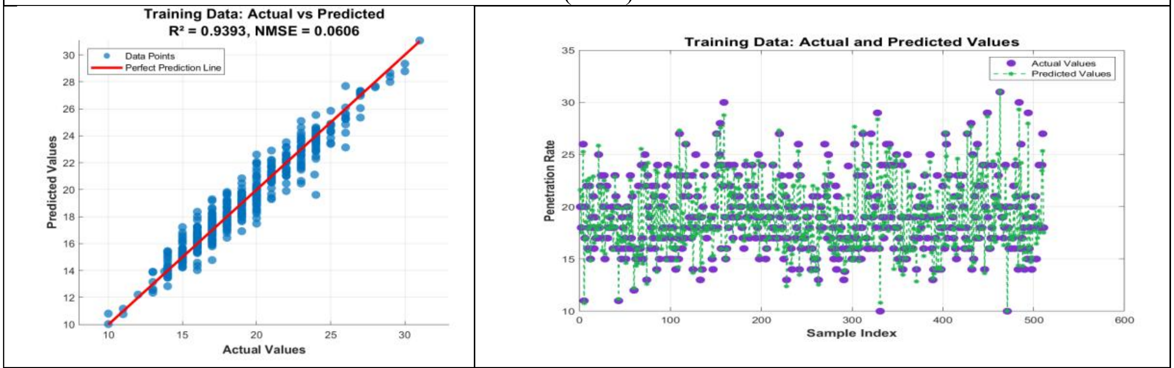
To evaluate the model's performance, the Normalized Mean Squared Error (NMSE) was adopted as the primary fitness function for the optimization algorithm. The NMSE was chosen for its property of being a dimensionless metric, allowing for interpretable comparison across different datasets. The coefficient of determination (R^2) provided a supplementary measure of the model's goodness-of-fit ([30], [31], [32]).

$$NMSE = \frac{MSE}{\sigma^2} = \frac{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sigma^2} \tag{21}$$

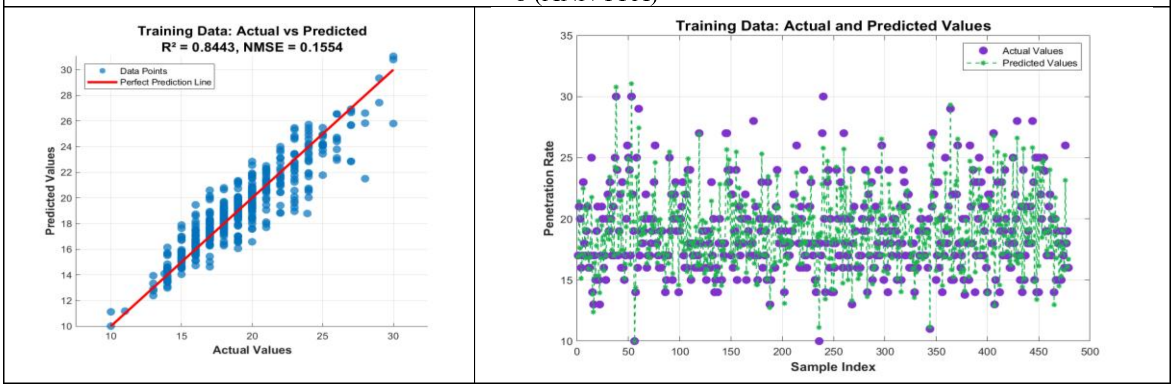
$$Determine\ coefficient \quad (R^2) = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y}_i)^2} \tag{22}$$



a (ANN)



b (ANN-FFA)



c (ANN-PSO)

Fig. 3. a: Comparison of predicted vs. actual values for the training dataset via the artificial neural network (ANN) model, b: the hybrid ANN-firefly algorithm (ANN-FFA) model, c: the hybrid ANN-particle swarm optimization (ANN-PSO) model.

Where y_i is the observed value, $\hat{y}_i$ is the predicted value, $\bar{y}_i$ is the mean of observed values, n is the number of data points, and σ^2 is the variance of the observed values.

II. RESULTS

A. Artificial Neural Network Training and Test Results

Based on the provided plots, the performance of the artificial neural network (ANN) model in predicting the rate of penetration (ROP) and other target variables was evaluated. For the training data, the ANN model demonstrated a strong fit, achieving a coefficient of determination (R^2) of 0.77 and an NMSE of 0.22, indicating good alignment between the predicted and observed values. The strong agreement between predicted and actual values on the training data is evident in Figure 4(a), where the fitted regression line aligns closely with the ideal y=x line. On the test data (Figure 4(b)), the model achieved an R^2 of 0.76 and an NMSE of 0.2377. These metrics indicate reasonable generalization performance, albeit with increased prediction error compared to the training results. These findings suggest that the ANN model has a satisfactory predictive ability for the target variables. However, further optimization of parameters or the integration of hybrid approaches, such as metaheuristic algorithms, may be needed to increase accuracy and reduce errors.

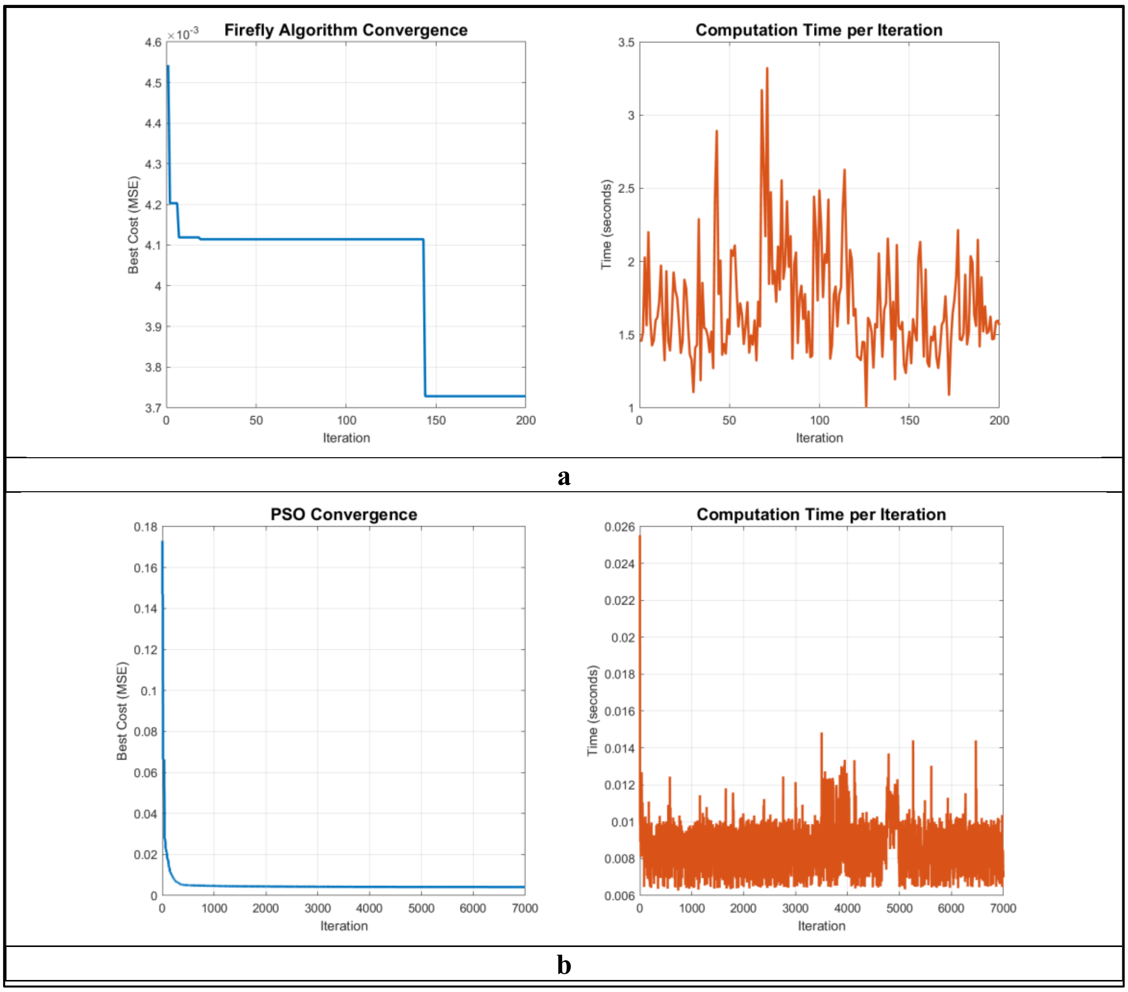


Fig. 4. Convergence plot of a: the Firefly Algorithm (FA), b: Particle Swarm Optimization (PSO) algorithm used optimize the Artificial Neural Network (ANN) model

B. Hybrid artificial neural network-firefly algorithm training and test results

The predictive performance of the hybrid artificial neural network-firefly algorithm (ANN-FFA) model was thoroughly evaluated via the provided plots, with a focus on its ability to estimate the rate of penetration (PR). For the training data, the ANN-FFA model achieved a coefficient of determination (R^2) of 0.93 and an NMSE of 0.06, indicating its ability to predict the PR with minimal error accurately. This evident in the training plots in Figure 4 (a), where the predicted values closely align with the actual values along the ideal y=x line. The model demonstrated strong generalization on the test data (Figure 4c), achieving an R^2 of 0.9 and an NMSE of 0.091. These results confirm its robustness and predictive accuracy on unseen data. The convergence plot in Figure 5 further highlights the efficiency of the firefly algorithm in optimizing the ANN parameters, as the cost function consistently decreases over iterations, ensuring efficient model training. These results highlight the ANN-FFA model as a powerful and reliable approach for predicting PR, offering superior performance compared with traditional ANN models in addressing complex, nonlinear engineering challenges.

C. Hybrid Artificial Neural Network-Particle Swarm Optimization Train and Test Results

The hybrid artificial neural network-particle swarm optimization (ANN-PSO) model was evaluated for its predictive performance in estimating the rate of penetration (ROP), as demonstrated by the provided plots. On the training data, the hybrid ANN-PSO model demonstrated exceptional performance, evidenced by a coefficient of determination (R^2) of 0.864 and a root mean square error (NMSE) of 0.122. These metrics indicate an excellent fit between the model's predictions and the observed values. The strong model fit is visually confirmed in the training data scatter plot (Figure 6(b)), where the regression line closely follows the line of perfect agreement (y = x). For the test data in Figure 6, the model maintained robust performance, with an R^2 of 0.84 and an NMSE of 0.15, indicating reliable generalizability to unseen data despite a slight increase in prediction error. The convergence plot (Figure 5) further emphasizes the efficiency of the PSO algorithm in fine-tuning ANN parameters, as the cost function steadily decreases across iterations. These

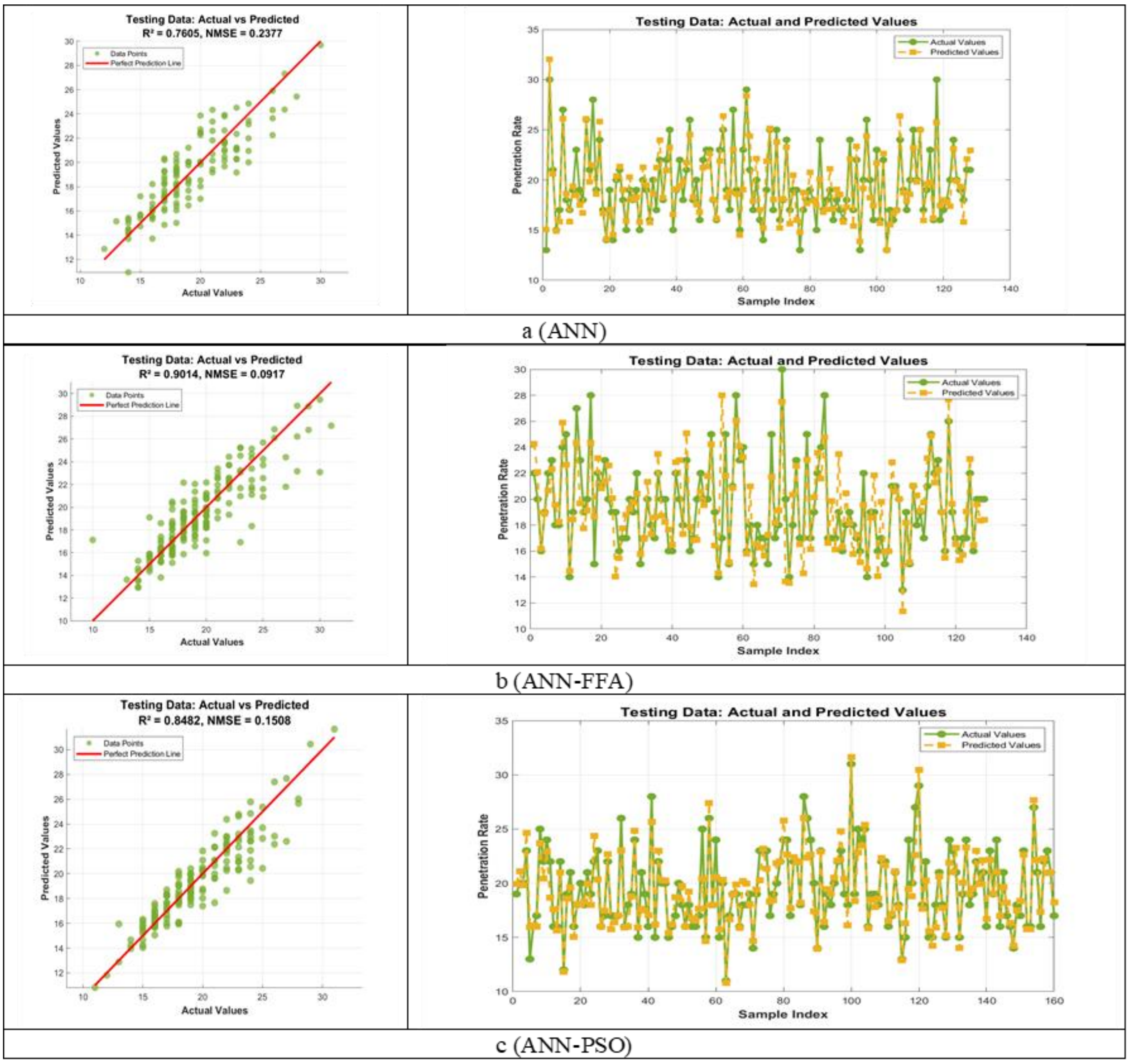


Fig. 5. Comparison of predicted vs. actual values for the test dataset using the artificial neural network (ANN) model, b: the hybrid ANN-firefly algorithm (ANN-FFA) model, c: the hybrid ANN-particle swarm optimization (ANN-PSO) model.

findings highlight the improved predictive power and consistency of the hybrid ANN-PSO model, establishing it as a more effective solution than conventional ANN models for addressing intricate prediction tasks in engineering contexts.

The penetration rate is a key factor in tunnelling operations and directly influences project duration, cost, and efficiency. This study developed predictive models for the penetration rate (PR) by leveraging optimization algorithms—specifically, particle swarm optimization (PSO) and the firefly algorithm (FA)—to refine the mathematical relationship between a set of input parameters and the PR. Two main groups of factors influence the penetration rate: geological parameters (e.g., the soil friction angle, cohesion, specific weight, shear modulus, and groundwater level) and machine parameters (e.g., torque, thrust force, and cutterhead rotation speed). These factors were incorporated into an initial mathematical model, which was subsequently optimized using both PSO and FA. The objective of this optimization was to minimize the normalized mean squared error (NMSE), which served as the goodness-of-fit function.

The results demonstrate that both metaheuristic algorithms significantly enhanced the model's predictive accuracy. However, the Firefly Algorithm (FA) demonstrated superior performance over Particle Swarm Optimization (PSO), achieving a higher coefficient of determination (R^2) and a lower normalized mean squared error (NMSE). This superior performance can be attributed to the FA's ability to balance exploration and exploitation in the search space, enabling it to find better solutions than PSO does. The inherent adaptability and efficiency of the FA in handling complex, nonlinear relationships likely contributed to its enhanced performance in optimizing the penetration rate model.

A direct comparison of the predictive performance (R^2) between the models developed in this study and those from previous influential works reveals critical contextual differences. While the Fuzzy Logic model by Ghasemi et al. (2014) and the ANN model by

TABLE I. COMPARISON OF PREDICTIVE MODEL PERFORMANCE FOR TBM PENETRATION RATE IN VARIOUS GROUND CONDITIONS.

Study	*Model Used*	*Geology Type*	*Key Input Parameters*	*R²*	*Error*	*Value*	*Notes*
Yagiz & Karahan (2011)	PSO-NLR	Hard Rock	UCS, Brittleness, Joint Spacing	0.94			Laboratory/Case Study in Rock
Salimi et al. (2016)	FL LMR NLMR PSO	Hard Rock	UCS, RQD, BTS	89.06 70.39 61.37 69.64	RMSE	0.13 0.22 0.34 0.21	Focus on hard rock conditions
Ghasemi et al. (2014)	Logic	Hard Rock	UCS, BI, DPW, Alpha Angle	0.893		-	Queens Tunnel, USA. High accuracy in hard rock.
Yagiz et al. (2009)	NLMR	Hard Rock	UCS, BI, DPW, Alpha Angle	0.82	RMSE	0.114	Queens Tunnel, USA. Best-performing regression model.
Yagiz et al. (2009)	ANN	Hard Rock	UCS, BI, DPW, Alpha Angle	0.95 (Train)	RMSE	0.066	Queens Tunnel, USA. High performance on training data.
Gholamnejad & Tayarani (2010)	ANN	Hard Rock	UCS, RQD, DPW	0.94	Mse	Min 0.16	Combined data from 3 tunnels. Complex 5-layer network.
Darbor et al. (2020)	ANFIS	Mixed Soil/Rock	Cohesion, Friction Angle, Torque, Thrust	0.87	RMSE	0.94	-
Present Study	ANN (Baseline)	Mixed Soil/Rock	Cohesion, Friction Angle, Torque, Thrust	0.764	NMSE	1.685	Test data performance
Present Study	ANN-PSO	Mixed Soil/Rock	Cohesion, Friction Angle, Torque, Thrust	0.78	NMSE	0.16	Test data performance
Present Study	ANN-FFA	Mixed Soil/Rock	Cohesion, Friction Angle, Torque, Thrust	0.836	NMSE	0.147	Test data performance

Gholamnejad & Tayarani (2010) achieved notably high R^2 values of 0.893 and 0.94 respectively, it is

imperative to note that these models were developed for and applied to hard rock conditions using parameters like Uniaxial Compressive Strength (UCS), Brittleness Index (BI), and Rock Quality Designation (RQD) [15, 33]. In contrast, the present study addresses the inherently more complex and stochastic nature of

mixed soft ground and soil-like formations encountered

in the Tabriz Metro Line 2 project. Predictive modeling in such conditions deals with greater inherent uncertainty, which often results in a lower ceiling for

predictive accuracy metrics like R^2. The primary achievement of this research is not the absolute R^2 value but the significant relative improvement achieved

by integrating metaheuristic algorithms (PSO and FA) with a baseline ANN model. Our hybrid ANN-FFA model improved the test data prediction from an R^2 of 0.76 (baseline ANN) to 0.90, demonstrating a powerful enhancement in predictive capability for challenging soft-ground tunneling environments. This performance is highly competitive when contextualized within the appropriate geotechnical domain, underscoring the effectiveness of our optimization approach for real-world, complex ground conditions.

These findings align with previous research emphasizing the efficacy of metaheuristic algorithms for solving complex engineering problems. The integration of FA with the predictive model not only improved accuracy but also provided a more robust framework for understanding the interaction between geological and machine parameters in tunnelling operations. This particularly important in tunnelling, where the interplay between ground conditions and machine performance is inherently complex and nonlinear.

Despite its promising performance, the proposed methodology is subject to several limitations. The computational complexity of the FA, while effective, may require more resources than simpler algorithms such as PSO. Additionally, the model's performance is highly dependent on the quality and quantity of input data, emphasizing the need for comprehensive and accurate datasets in real-world applications.

This study demonstrates the significant potential of advanced metaheuristic optimization algorithms, notably the Firefly Algorithm (FA), for enhancing the prediction accuracy of penetration rates in tunnelling operations. Future research could explore the integration of additional metaheuristic algorithms or hybrid approaches to further improve the predictive accuracy. Moreover, applying these models to real-world tunnelling projects and incorporating real-time data could validate their practical utility and expand their applicability within the discipline of geotechnical engineering.

III. 5. Conclusion

This study investigates the application of advanced optimization techniques, particle swarm optimization (PSO) and the firefly algorithm (FA), for the predictive modeling of the penetration rate in tunnelling operations. By categorizing the influencing factors into geological parameters (e.g., the soil friction angle, cohesion, specific weight, shear modulus, and groundwater level) and machine parameters (e.g., torque, thrust force, and cutterhead rotation speed), a mathematical relationship was established and optimized to minimize the normalized mean squared error (NMSE). The results demonstrated that both the PSO algorithm and the FA significantly enhanced the predictive accuracy of the model, with the firefly algorithm outperforming the PSO algorithm in terms of higher (R^2) values and lower NMSE. This superior performance is attributed to the FA's efficient exploration-exploitation balance and its ability to handle complex, nonlinear relationships more effectively.

The findings underscore the importance of integrating metaheuristic optimization algorithms into predictive models for tunnelling operations, as they provide a robust framework for understanding the intricate interactions between ground conditions and machine performance. Despite the FA-based model's exceptional performance, the study underscored that high-quality data and significant computational resources are prerequisites for ensuring its efficacy in real-world applications.

Future research could explore the integration of additional metaheuristic algorithms or hybrid approaches to refine the predictive accuracy further. Additionally, applying these models to real-world tunnelling projects and incorporating real-time data could validate their practical utility and expand their applicability in geotechnical engineering. This study advances the field of tunnelling optimization by introducing a reliable and efficient method for predicting penetration rates, which can be used to significantly improve tunnelling operations.

REFRENCES

[1] Project, T.M.L., *EPB TBM Cutter Head*. 2019.

[2] Benardos, A., *Artificial intelligence in underground development: a study of TBM performance.* Underground Spaces: Design, Engineering and Environmental Aspects, 2008. **102**: p. 121.

[3] Bazargan, S., et al., *Analysis of the Performance of Cutting Tools of Tunnel Boring Machine (TBM) in Silty-Sand Soils Using Artificial Neural Network (ANN) – Case Study: Tabriz Metro Line 2 Project.* Asian Journal of Water, Environment and Pollution, 2022. **19**(2): p. 71-78.

[4] Darbor, M., H. Chakeri, and M. Asgharzadeh Dizaj, *Investigation of the Effect of Different Parameters on the Penetration Rate of Earth Pressure Balance Boring Machine using Fuzzy and Neuro-Fuzzy Methods, and Metaheuristic Algorithms (A Case Study: Tabriz Metro Line 2).* Journal of Analytical and Numerical Methods in Mining Engineering, 2020. **10**(25): p. 43-60.

[5] Nickjou Tabrizi, A.H., et al., *The effect of TBM operational parameters on the wear of cutting tools using a tunnel boring machine laboratory simulator.* Journal of Analytical and Numerical Methods in Mining Engineering, 2022. **12**(33): p. 55-63.

[6] Khodaee Ashestani, S., et al., *Estimating Penetration Rate of Excavation Machine Using Geotechnical Parameters and Neural Networks in Tabriz Metro.* Journal of Analytical and Numerical Methods in Mining Engineering, 2023. **13**(37): p. 1-9.

[7] Khoshzaher, E., et al., *The effects of water content and grain size on the clogging and abrasivity of fine-grained soils in mechanized excavation.* Rudarsko-geološko-naftni zbornik, 2023. **38**(2): p. 65-74.

[8] Darbor, M., H. Chakeri, and T. Ansari, *The Influence of Soil Particle Size Distribution on the Abrasion of EPB Machine Cutting Tools.* Ferdowsi Civil Engineering, 2023. **35**(4): p. 17-34.

[9] 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.

[10] Amoun, S. and H. Chakeri, *Cutting Tools Wear in Soft Ground Tunneling: Field and Experimental Insights.* Journal of Mining and Environment, 2024. **15**(3): p. 1103-1129.

[11] Maleki, A., et al., *Experimental study of the effects of mechanical properties of rocks on wear of cutting tools using a new small-scale linear cutting machine (LCM).* Journal of Mining and Environment, 2025.

[12] Chakeri, H., et al., *Experimental and numerical investigation of the TBM disc cutter wear using a new tunnel boring machine laboratory simulator.* Heliyon, 2024. **10**(17): p. e37148.

[13] Chakeri, H., et al., *Laboratory and numerical investigation of cutting tool performance using a new small-scale linear cutting machine.* Scientific Reports, 2025. **15**(1): p. 22337.

[14] Yagiz, S., et al., *Application of two non-linear prediction tools to the estimation of tunnel boring machine performance.* Engineering

Applications of Artificial Intelligence, 2009. **22**(4): p. 808-814.
[15] Gholamnejad, J. and N. Tayarani, *Application of artificial neural networks to the prediction of tunnel boring machine penetration rate.* Mining Science and Technology (China), 2010. **20**(5): p. 727-733.
[16] Yagiz, S. and H. Karahan, *Prediction of hard rock TBM penetration rate using particle swarm optimization.* International Journal of Rock Mechanics and Mining Sciences, 2011. **48**(3): p. 427-433.
[17] Torabi, S.R., et al., *Study of the influence of geotechnical parameters on the TBM performance in Tehran–Shomal highway project using ANN and SPSS.* Arabian Journal of Geosciences, 2013. **6**(4): p. 1215-1227.
[18] Salimi, A., et al., *Application of non-linear regression analysis and artificial intelligence algorithms for performance prediction of hard rock TBMs.* Tunnelling and Underground Space Technology, 2016. **58**: p. 236-246.
[19] Gao, L. and X.-b. Li, *Utilizing partial least square and support vector machine for TBM penetration rate prediction in hard rock conditions.* Journal of Central South University, 2015. **22**(1): p. 290-295.
[20] Jamshidi, A., *Prediction of TBM penetration rate from brittleness indexes using multiple regression analysis.* Modeling Earth Systems and Environment, 2018. **4**(1): p. 383-394.
[21] 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**(2): p. 501-513.
[22] Yang, X.-S. *Firefly Algorithms for Multimodal Optimization*. 2009. Berlin, Heidelberg: Springer Berlin Heidelberg.
[23] Sayadi, M., R. Ramezanian, and N. Ghaffari-Nasab, *A discrete firefly meta-heuristic with local search for makespan minimization in permutation flow shop scheduling problems.* International Journal of Industrial Engineering Computations, 2010. **1**(1): p. 1-10.
[24] Łukasik, S. and S. Żak. *Firefly Algorithm for Continuous Constrained Optimization Tasks*. 2009. Berlin, Heidelberg: Springer Berlin Heidelberg.
[25] Yang, X.-S., *Nature-inspired metaheuristic algorithms*. 2010: Luniver press.
[26] Kennedy, J. and R. Eberhart. *Particle swarm optimization*. in *Proceedings of ICNN'95 - International Conference on Neural Networks*. 1995.
[27] Shi, Y. and R. Eberhart. *A modified particle swarm optimizer*. in *1998 IEEE International Conference on Evolutionary Computation Proceedings. IEEE World Congress on Computational Intelligence (Cat. No.98TH8360)*. 1998.
[28] Xinchao, Z., *A perturbed particle swarm algorithm for numerical optimization.* Applied Soft Computing, 2010. **10**(1): p. 119-124.
[29] Zhan, Z.H., et al., *Adaptive Particle Swarm Optimization.* IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 2009. **39**(6): p. 1362-1381.
[30] Draper, N., *Applied regression analysis*. 1998: McGraw-Hill. Inc.
[31] Slinker, B.K. and S.A. Glantz, *Primer of applied regression and analysis of variance*. 1990: McGraw-Hill.
[32] Steel, R. and J. Torrie, *Principles and procedures of statistics*. 1960: McGraw-Hill Book Company, Inc., New York, Toronto, London. xvi + 481 pp.
[33] Ghasemi, E., S. Yagiz, and M. Ataei, *Predicting penetration rate of hard rock tunnel boring machine using fuzzy logic.* Bulletin of Engineering Geology and the Environment, 2014. **73**(1): p. 23-35.

APPENDIX

Artificial neural networks (ANN)

Artificial neural networks (ANNs) are highly effective for solving nonlinear problems because of their adaptability, whereas logistic and linear regressions are valued for their efficiency and reliability in fitting data. However, linear models have limitations because they rely on linear functions, which restrict their ability to model complex, nonlinear relationships. To address this, linear models can be applied to transformed inputs via nonlinear functions, as illustrated in equation (1):

$$y(x, w) = f\left(\sum_{j=1}^{M} w_j \varphi_j(x)\right) \qquad (1)$$

Where a nonlinear transformation $\varphi(x)$ is applied to the input. In ANNs, the goal is to define a mapping $y = f\ (\boldsymbol{x};\ \boldsymbol{w})$ by learning adaptive parameters for basic functions, allowing the model to approximate complex relationships.

A basic neural network involves transforming input variables through linear combinations and $a_k = \sum_{i=1}^{M} w_{kj}^{(2)}\ z_i\ +\ w_{k0}^{(2)}$ activation functions. Equation (2) shows how input variables are combined with weights and biases to produce activations, which are then passed through nonlinear activation functions, as shown in Equation (3). Common activation functions include sigmoidal functions, although the rectified linear unit (ReLU) is often more efficient in modern applications.

$$a_j = \sum_{i=1}^{D} w_{ji}^{1} x_i + w_{j0}^{(1)} \tag{2}$$

$$z_j = h(a_i) \tag{3}$$

The outputs of these functions, called hidden units, are further combined in the next layer, as demonstrated in Equation (4), where the hidden units are linearly combined with weights and biases in the second layer.

$$a_k = \sum_{i=1}^{M} w_{kj}^{(2)} z_i + w_{k0}^{(2)} \tag{4}$$

The final network outputs are generated by applying an output activation function to the activations of the second (output) layer. For regression tasks, the identity function is often used as the activation function, whereas for binary classification, the sigmoid function (Equation (5)) is commonly applied. Equation (6) combines all stages to represent the overall network function for sigmoidal outputs, mapping input features to output labels via a set of adaptable parameters $\boldsymbol{w}$.

$$\sigma(a) = \frac{1}{1 + \exp(-a)} \tag{5}$$

$$y_k(x, w) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{1} x_i + w_{j0}^{(1)}\right) + w_{k0}^{(2)}\right) \tag{6}$$

The bias parameters can be simplified by introducing an additional input feature $x_0 = 1$, as shown in Equation (7), and Equation (8) provides a concise representation of the network function, incorporating biases.

Figure 3 illustrates the architecture of a two-layer neural network, depicting the bias nodes in each layer: x_0 for the input layer and z_0 for the hidden layer.

$$a_j = \sum_{i=1}^{D} w_{ji}^{(1)} + x_i \tag{7}$$

$$y_k(x, w) = \sigma\left(\sum_{j=1}^{M} w_{kj}^{(2)} h\left(\sum_{i=1}^{D} w_{ji}^{(1)} x_i\right)\right) \tag{8}$$

The flexibility of artificial neural networks (ANNs) allows them to model complex, non-linear relationships beyond the capability of linear models. Through the learning of adaptive parameters, ANNs can effectively approximate highly nonlinear functions. The flexibility of ANNs allows them to model complex relationships that linear models cannot capture, and by learning adaptive parameters, ANNs can approximate highly nonlinear functions effectively. The choice of activation function (e.g., sigmoid or ReLU) significantly impacts network performance. Modern functions like ReLU have notably improved training efficiency and convergence. The generalization ability of a neural network depends on the proper tuning of its weights, biases, and activation functions; this capability makes the ANN framework robust for modeling complex, nonlinear relationships in data.

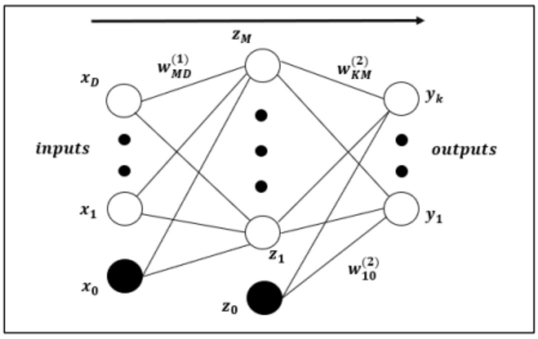


Fig. 6 . Network diagram for a two-layer neural network.

نشریه‌ی مکانیک سنگ
JOURNAL OF ROCK MECHANICS
دوره نهم، شماره۱، بهار ۱۴۰۴، صفحه ۴۷ تا ۶۰
https://doi.org/10.22034/IRSRM.2025.540267.1054

تخمین نرخ نفوذ ماشین حفاری تونل با استفاده از شبکه عصبی بهینه شده با الگوریتم‌های بهینه‌سازی ازدحام ذرات و کرم شب‌تاب، مطالعه موردی: خط ۲ متروی تبریز

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دریافت: ۱۴۰۴/۰۱/۲۵؛ پذیرش: ۱۴۰۴/۰۳/۳۱

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چکیده

نرخ نفوذ (PR)، یک پارامتر حیاتی در تونل‌سازی است، زیرا مستقیماً زمان‌بندی پروژه، هزینه و کارایی کلی را تعیین می‌کند. توسعه مدل‌های پیش‌بینی دقیق برای نرخ نفوذ (PR) به منظور بهینه‌سازی عملکرد تونل‌سازی و برنامه‌ریزی مؤثرتر پروژه بسیار مهم است. برای پاسخ به این نیاز، این مطالعه، از الگوریتم‌های بهینه‌سازی فراابتکاری پیشرفته برای تقویت یک شبکه عصبی مصنوعی (ANN) به منظور بهبود پیش‌بینی نرخ نفوذ (PR) استفاده می‌کند. به طور خاص، از بهینه‌سازی ازدحام ذرات (PSO) و الگوریتم کرم شب‌تاب (FA) برای افزایش دقت مدل استفاده شد. این تحقیق از داده‌های پروژه خط ۲ متروی تبریز بهره گرفت. داده‌ها، شامل عوامل کلیدی تأثیرگذار بودند که به شرح زیر دسته‌بندی شدند: پارامترهای زمین‌شناسی شامل زاویه اصطکاک داخلی خاک، چسبندگی، وزن مخصوص، مدول برشی و عمق سفره آب زیرزمینی و پارامترهای ماشین حفاری شامل گشتاور، نیروی رانش و سرعت چرخش. هدف صریح بهینه‌سازی مدل، به حداقل رساندن خطای میانگین مربعات نرمال‌شده (NMSE) برای پیش‌بینی‌های آن در مقایسه با مقادیر واقعی اندازه‌گیری‌شده بود. نتایج، نشان داد که هر دو الگوریتم PSO و FA، عملکرد پیش‌بینی مدل پایه ANN را به طور قابل توجهی افزایش می دهند. با این حال، الگوریتم کرم شب‌تاب، بهتر عمل کرد و به ضریب تعیین بالاتر (۰/۹ برای داده‌های آزمون، در مقایسه با ۰/۸۴ برای مدل بهینه‌سازی‌شده با PSO) و NMSE پایین‌تر دست یافت. این نتیجه کلیدی به قابلیت‌های جستجوی قوی FA نسبت داده می‌شود که اثربخشی آن را در شناسایی پارامترهای بهینه مدل برای روابط پیچیده و غیرخطی در تونل‌سازی تأیید می‌کند. این یافته‌ها، یک چارچوب قابل اعتماد و مبتنی بر داده برای پیش‌بینی عملکرد TBM ارائه می‌دهد که ارزش عملی قابل توجهی برای برنامه‌ریزی و اجرای پروژه در مهندسی ژئوتکنیک دارد.

واژگان کلیدی

شبکه عصبی مصنوعی (ANN)، الگوریتم کرم شب تاب (FA)، بهینه سازی ازدحام ذرات (PSO)، TBM EPB، پیش بینی نرخ نفوذ، متروی تبریز، پارامترهای مکانیک خاک