Shahrood University of Technology

Journal of Mining and Environment (JME)

Journal homepage: www.jme.shahroodut.ac.ir

Iranian Society of Mining Engineering (IRSME)

Application of Intelligent Methods in Predicting Penetration Rate of Drill Bits in Open-Pit Mining

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Article Info

Received 16 March 2025
Received in Revised form 21 May 2025
Accepted 30 June 2025
Published online 30 June 2025

DOI: 10.22044/jme.2025.15933.3065

Keywords

Drilling
Rate of penetration
Intelligent methods
Adaptive moment estimation
Stochastic gradient descent

Abstract

Drilling is one of the most important operations in open-pit mining, and the penetration rate of drill bits is a key performance measure. This paper presents research on the penetration rate of drill bits based on mining rock mass rating, thrust pressure (weight on bit), rotational pressure, and Schmidt hammer rebound hardness. To achieve this, a dataset comprising the drilling operations of 85 blastholes from the Sungun copper mine in Iran was prepared and analyzed using statistical and intelligent methods. Multivariate regression analysis and artificial neural networks developed in Python, utilizing optimization algorithms such as gradient descent, stochastic gradient descent, and adaptive moment estimation, were applied to predict the penetration rate of drill bits in this study. The coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE) served as performance indicators to evaluate the methods employed. Among these, the adaptive moment estimation (Adam)-based model exhibited superior performance compared to alternative models, achieving values of $R^2 = 0.96$, MAE = 4.55, and RMSE = 4.30. Furthermore, the sensitivity analysis revealed that mining rock mass rating is the most influential factor on the rate of penetration, while thrust pressure has the least impact.

1. Introduction

Drilling is one of the most critical operations in mining and civil construction, where performance hinges on key factors such as the rate of penetration (ROP) and specific energy consumption. Since the 1950s, rate of penetration prediction has been a focal point of research due to its direct impact on mining costs. Researchers have investigated the influence of various parameters on rate of penetration and developed empirical models through experimental studies. For instance, Graham and Muench [1] proposed a mathematical model relating rate of penetration based on weight on bit (WOB), depth, and rotary speed. Maurer [2], meanwhile, established penetration rate correlations for roller-cone bits based on weight on bit, rotary speed, and rotational pressure (RP). Technical studies emphasize that rate of penetration assessment depends on three primary categories: (1) rock properties (e.g., uniaxial compressive strength, hardness, fracture density, and point load index), (2) operational parameters (e.g., weight on bit and rotational pressure), and (3) bit mechanics (e.g., type, design, wear, and condition).

Statistical approaches, including multivariate regression and machine learning models, have been widely employed for ROP prediction. Galle and Woods [3] incorporated variables such as weight on bit, rotary speed, formation type, and bit wear, while Bourgoyne and Young [4] optimized operational parameters (rotational and thrust pressure, bit diameter, and formation pressure) using multiple regression on extensive datasets. Fear [5] introduced numerical correlations for ROP that integrated bit characteristics, geological data, and mud logging. Bilgin et al. [6] developed regression-based models to predict penetration rates (PR) in diverse rock formations. Their work

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included numerical examples illustrating the effects of independent variables on penetration rates for impact hammers, large-diameter drill rigs, and boring machines. Hoseinie et al. [7] analyzed the penetration rate of pneumatic top hammer drills using laboratory tests of rock properties, establishing correlations between ROP and uniaxial compressive strength, tensile strength, elastic modulus, dry density, and Schmidt hammer rebound number through regression analysis. Additional studies have examined relationships between ROP and individual factors such as weight on bit [8], rotary speed [9], and flow rate [10]. Uniaxial compressive strength (UCS) has emerged as a key factor in drilling performance, with applications extending beyond geological and geotechnical engineering [11,12]. Tiryaki [13] highlighted that accurate UCS measurement and prediction can reduce drilling costs, positioning UCS as a central focus of ROP-related research [14–18]. While multivariate regression-based studies have yielded moderate correlations for ROP prediction [19–22], Khosravimanesh et al. [23] advanced this field by applying linear, lasso, and ridge regression models.

Following the increasing popularity of machine learning methods, fuzzy models [14, 24–28], artificial neural networks (ANNs) [29–35], and neuro-fuzzy inference systems [19, 35–37] have become robust tools for rate of penetration prediction. Kamran [38] employed decision tree, adaptive boosting, and random forest algorithms with input parameters such as brittleness, UCS, and Brazilian tensile strength. Saeidi et al. [20] utilized Monte Carlo simulations, whereas others explored multilayer perceptrons, support vector regression, and random forests to enhance accuracy [39,40]. Mebarkia et al. [41] evaluated rate of penetration at Algeria's Boukhdra iron ore mine using regression analysis, ANNs, and fuzzy logic, incorporating compressive strength, thrust pressure, and rotational pressure as inputs. Their findings demonstrated the superior adaptability and generalization of ANN models over regression and fuzzy logic. In Iran's Sarcheshmeh copper mine, extreme gradient boosting (XGBoost) algorithms optimized by metaheuristic methods (Harris hawk optimization, grid search, random search, and dragonfly algorithm) were applied to assess rotary drilling penetration rates [42]. This study treated UCS, tensile strength, joint direction, and joint spacing as dependent parameters, revealing the hybrid dragonfly algorithm–XGBoost method as the most effective predictor. Shi et al. [43] further proposed a genetic algorithm–light gradient boosting machine combination as an optimal intelligent model for ROP prediction.

This study evaluates rate of penetration using multivariate regression and ANN models implemented in Python, analyzing field data from drilling machines (Atlas Copco, Husherr, Sunward, Tamrock) at Iran's Sungun copper mine. Prior studies identify six key parameter categories influencing ROP: (1) drill bit characteristics (type, design, wear), (2) mechanical parameters (thrust pressure, rotational pressure), (3) rock properties (hardness, abrasiveness, fractures), (4) operational practices (feed rate, alignment, vibration control), (5) environmental conditions (depth, temperature, pressure), and (6) human/technological factors (operator skill, automation) [44,45]. For this work, thrust pressure, rotational pressure, Schmidt hammer rebound, and mining rock mass rating (MRMR) were selected as predictors, aligning with common parameters in existing literature. The research combines empirical fieldwork with laboratory analyses, emphasizing methodological rigor through systematic evaluation of joint and discontinuity conditions across mining faces to determine MRMR. The ANN model was optimized using gradient descent, stochastic gradient descent, adaptive gradient algorithm, and adaptive moment estimation.

2. Case study

The Sungun copper complex is situated in East Azerbaijan Province, Iran, near Varzaghan city, at geographical coordinates 38° 43′ 00″ N latitude and 46° 43′ 38″ E longitude. The complex lies 25 km northwest of Varzaghan and approximately 100 km northeast of Tabriz. The region exhibits an average elevation of 2,000 meters above sea level (masl), with local topographic relief reaching a maximum of 2,700 masl (Figure 1). Hydrothermal alteration constitutes a dominant geological process in the mine's vicinity. Mineralization within the Sungun porphyry deposit is predominantly hosted by hydrothermally altered quartz-monzonite lithological units. Feldspar minerals within the deposit have undergone pervasive alteration, resulting in the formation of sericite and kaolinite. The primary ore minerals identified at Sungun include molybdenite (MoS_2), pyrite (FeS_2), and chalcopyrite ($CuFeS_2$) [46].

Figure 1. The location and a viwe of Sungun copper mine in Iran

3. Data description

This study introduces a user-centric, rapid-deployment rate of penetration prediction system designed for practical field implementation in mining engineering. Through structured consultations with mine personnel and drilling operators, critical operational parameters influencing ROP were identified, building upon prior research frameworks. The dataset underpinning this analysis derives from 85 blastholes drilled at the Sungun copper complex using four distinct rigs: Husherr, Tamrock 1500, Sunward-SWDE 200, and Atlas Copco ROC L8, with sample sizes of 19, 23, 21, and 22 blastholes, respectively (Figures 2–3).

Operational specifications for these rigs, including thrust pressure (representative for weight on bit), rotation pressure (RP), Mining Rock Mass Rating (MRMR), and Schmidt hammer rebound hardness, are systematically tabulated in Table 1. Table 2 summarizes the statistical distribution of the dataset, encompassing sample size (N), mean, maximum, minimum, and standard deviation values for each parameter.

Figure 2. A view of Atlas Copco ROC L8

Figure 1. A view of Sunward-SWDE200

Table 1. Operational specifications of the equipment

N	Machine	Min - Max rotational pressure (psi)	Min - Max thrust pressure (psi)	Bit type	Bit diameter (inch)
1	Atlas Copco	600 -1000	1500-1800	Flat face	6.5
2	Husherr	1900-2200	1500-1700	Flat face	6.5
3	Sunward	600-780	600-750	Flat face	6.5
4	Tamrock	600-800	2000-2200	Flat face	6.5

Table 2. Descriptive statistics of the considered parameters

	Thrust pressure (psi)	Rotational pressure (psi)	Schmidt hammer rebound	MRMR	ROP (m/h)
N	85	85	85	85	85
Avg	1118	1427	37.22	40.89	38.28
Max	1800	2200	70	84	101.25
Min	600	600	20	15	10.13
Std.Dev	481.68	681.19	10.44	12.13	22.13

3.1. Thrust Pressure

Empirical studies demonstrate that weight on bit or thrust pressure (ThP) exerts a critical influence on rate of penetration in rock mass drilling [47–49]. Optimal thrust pressure varies with lithological and operational conditions, as deviations from ideal thresholds impair drilling efficiency. Excessive thrust pressure can induce insufficient airflow for bit cooling, while inadequate value promotes inefficient energy transfer [20].

3.2. Rotational Pressure

Rotational pressure (RP), a key operational parameter in rotary drilling systems, directly correlates with rock drillability and rate of penetration optimization. Increased rotational speed enhances ROP by improving cuttings removal and reducing frictional energy losses [50–52]. This relationship is mechanistically tied to the specific energy required for rock fragmentation, where higher RP amplifies shear stress at the rock-bit interface [53]. Notably, Kahraman [48] established RP (rather than rotational speed alone) as a robust predictor variable in ROP modeling, emphasizing its sensitivity to heterogeneous rock mass conditions.

3.3. Mining Rock Mass Rating

Accurate prediction of the rate of penetration requires all-inclusive integration of field-specific drilling parameters. In this study, the mining rock mass rating (MRMR) system was applied as a predictive parameter due to its adaptability across diverse geo-mechanical and operational conditions. Globally, mining operations have employed rock mass classification systems, such as the in-situ rock mass rating (IRMR), for decades to evaluate jointed rock masses. Despite advancements in complex computational design workflows (e.g., finite element modeling and computer-aided design packages), MRMR persists as a versatile and practical framework for preliminary mine design. However, sophisticated analytical methods should complement—not replace—rock mass classification systems. As it has been noted in various geotechnical literature, while classification systems are occasionally perceived as overly simplistic for terrain assessment, they remain indispensable practical tools for engineering decision-making. Crucially, MRMR must be iteratively applied throughout the mine lifecycle, from exploration to closure, to ensure geomechanical stability and operational efficiency [54].

3.4. Schmidt Hammers Rbound Hardness

The Schmidt hammer (Sch) is a portable, cost-effective index testing device widely utilized for rebound hardness (R-value) measurements in both laboratory and in situ settings. Its primary applications include estimating the uniaxial compressive strength and elastic modulus of intact rock specimens. Beyond material characterization, Sch-derived R-values inform critical operational parameters in quarrying, drilling, and tunneling by quantifying:

Excavatability: Rock resistance to mechanical cutting or fragmentation.

Boreability: Drillability indices for rotary or percussive systems.

Discontinuity wall strength: UCS estimates for fracture surfaces in jointed rock masses [55].

4. Methodology

4.1. Multiple linear regression

The Multiple Linear Regression (MLR) technique was employed to develop predictive models for rate of penetration, accounting for the complex interdependencies between independent parameters (RP, ThP, Sch rebound hardness, and MRMR). MLR-based analysis was selected over nonlinear methods due to its interpretability and suitability for modeling linear relationships in geomechanical systems. Spearman correlation analysis was utilized to assess the independence of input variables, with a conservative threshold of $r < 0.6$ adopted to define not strong correlations between paired parameters.

This non-parametric approach complements Pearson correlation by accommodating non-linear relationships and ordinal data, ensuring robustness in geomechanical datasets where normality assumptions may not hold [56].

4.2. Artificial Neural Network (ANN)

ANNs are computational networks that simulate the system of brain neurons in living organisms. Such networks are designed based on the biological scientists' current knowledge of neural neuron activity. In a neural network, nodes or neurons are the smallest computing units that process input data to obtain the output. A neural connection is a vector connecting the processing units of one layer to those of the next layer (Figure 4). Each neuron has a specific weight that can be adjusted based on the information transmitted between them. Neurons are organized in layers (first layer including considered inputs, last layer including the output and hidden layers) within an ANN [57-60]

Educational training is essential for neural networks as it supplies the training data needed to adjust the network's weights, allowing the model to learn how to effectively map inputs to outputs. This process encompasses the patterns and structures present in the training datasets, along with rule-based objectives that are differentiable concerning the network's parameters, steering the learning through gradient-based optimization techniques and aiding in informing the models' predictions and decisions. However, without attention to the applicable method, learning is generally a repetitive procedure [61].

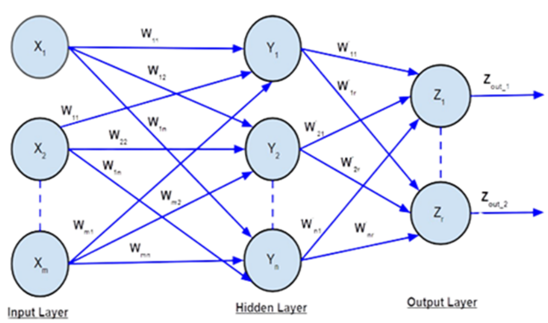


Figure 4. The structure of a simple ANN

ANNs offer two significant advantages. The first is their ability to serve as a substitute for complex simulation software packages that require extensive processing time. With ANNs, software can learn its behavior and generate results with reduced effort. Furthermore, ANNs can establish meaningful relationships within large datasets and predict outcomes for unfamiliar cases [32]. A neural network is created using a combination of training and testing data. The training data is utilized to train the ANN and adjust its parameters, while the test data is employed to evaluate the accuracy of the predictive model [62].

In the context of neural networks, training is one of the most crucial components. A learning algorithm focuses on adjusting and optimizing the weights and biases of the network to ensure it achieves the best output based on what the algorithm aims to learn. There are two primary categories of learning methods: unsupervised and supervised. [57, 63].

Multi-layered perceptron (MLP) is a type of ANN architecture that comprises fully connected neurons in feed-forward networks. In terms of robustness and performance, MLP is among the most widely used ANN architectures, whether for research or practical applications. Based on the generalization of the mean square algorithm and the error correction law, these algorithms fall under the category of batch algorithms. In this process, the network's output is compared to the target output to calculate the approximation error. The error is then propagated through the network, and the weights and biases are adjusted so that the network's outputs align more closely with reality [64].

4.3. Stochastic Gradient Descent (SGD)

Stochastic gradient descent (SGD) is a "classic" optimization algorithm in which each layer of the network is assigned its own weight when calculating the gradient of the network's cost function. Whenever forward processing through the network occurs, a cost function parameter is generated. Subsequently, a new weight is established in the network by multiplying each gradient by the learning rate (Equation 1)[65].

$$\theta = \theta - \eta \cdot \nabla_\theta J(\theta; x^{(i)}; y^{(i)}) \qquad (1)$$

Where ∇_θ and η represent the gradient operator and learning rate, respectively and $J(\theta; x^{(i)}; y^{(i)})$is known as the objective function (loss function or error function) based on training samples (including inputs, $x^{(i)}$, and outputs, $y^{(i)}$).

4.4. Adaptive Gradient Algorithm (Adagrad)

As an algorithm for gradient-based optimization, the Adagrad adaptive gradient algorithm utilizes this approach: it modifies the learning rate based on the parameters, applying larger adjustments for parameters with lower occurrence rates, while providing smaller adjustments for parameters with higher occurrence rates. Consequently, it is particularly effective for computations on sparse data. The reliability of the SGD method has been significantly enhanced by Adagrad [66].

$$\theta_{t+1,i} = \theta_{t,i} - \eta \cdot G_t^{-0.5} g_{t,i} \quad (2)$$

Where, η is the learning rate, G_t signifies the sum of the squares of the of each diagonal element i, i of the θ_i up to time step t, and $\theta_{t,i}$ is the gradient of the objective function at time t.

4.5. Adaptive Moment Estimation (Adam)

Adam is an algorithm that optimizes stochastic objective functions using gradient-based first-order optimization. This algorithm adaptively estimates a lower-order moment. Iterative weight updating is employed to train machine learning models through Adam, which can be viewed as an extension of stochastic gradient descent. In a conventional adaptive gradient algorithm, all weight updates rely on a constant learning rate (Lr). By adaptively adjusting the Lr parameter, the Adam algorithm seeks to enhance the model training phase [67].

$$m_t = \beta_1 m_{(t-1)} + (1-\beta_1) g_t \quad (3)$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \quad (4)$$

$$\widehat{m}_t = \frac{m_t}{1-\beta_1^t} \quad (5)$$

$$\hat{v}_t = \frac{v_t}{1-\beta_2^t} \quad (6)$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon} \widehat{m}_t \quad (7)$$

Where β_1 and β_2 are two hyperparameters, m_t and v_t are moving averages of the gradients, g_t is the gradient at time t, and ε as a smoothing term avoids the division by zero.

5. Results and Discussion

Spearman's correlation analysis was conducted to evaluate interdependencies among variables, with statistical significance assessed for the developed predictive models. Figure 5 displays the correlation matrix generated through Spearman's rank-order correlation coefficient calculations. The results reveal no statistically significant correlations (r < 0.6) between independent variables (Thrust pressure, rotational pressure, Mining rock mass rating, and Schmidt hammer hardness), confirming the absence of multicollinearity. Consequently, the dataset was validated as suitable for advanced analytical workflows, including regression and machine learning applications.

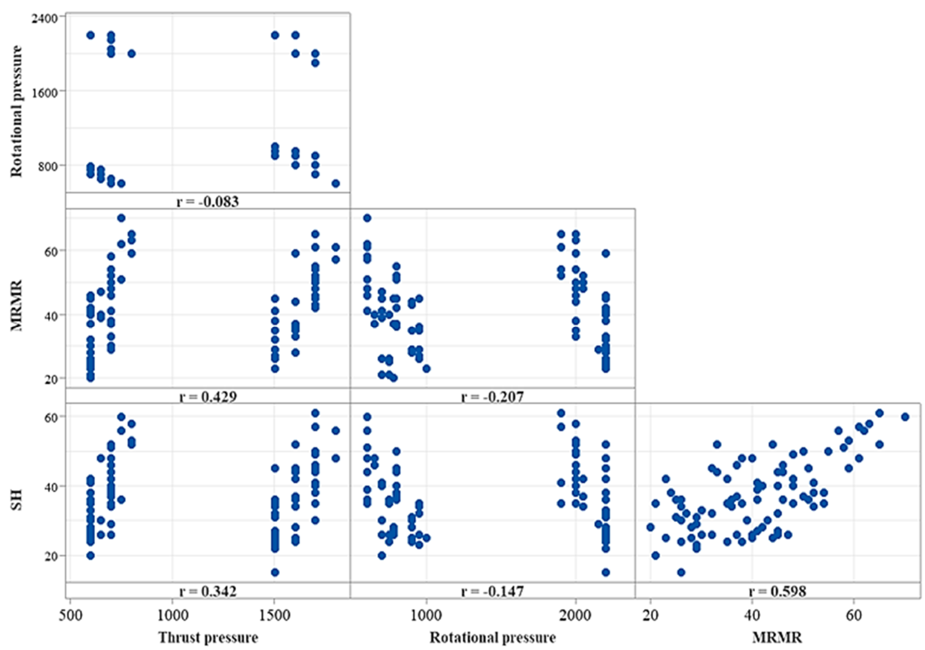


Figure 5. Correlation matrix for considered data set

A linear correlation analysis was performed to quantify the relationship between rate of penetration and key operational parameters (ThP, RP, MRMR, Sch) for each drilling machines. Multivariate regression models were subsequently developed for Atlas Copco ROC L8, Husherr, Tamrock-1500, and Sunward-SWDE200 yielding R^2 values of 89.4%, 89.3%, 83.7%, and 91.6%, respectively. The results, illustrated in Figure 6, confirming the efficacy of multivariate regression in assessing ROP when applied to comprehensive operational datasets.

Equation (8) presents the multivariate regression output with an R² of 73.9% based on 20% of randomly selected data from the entire database, which is not entirely acceptable. This imprecision arises from the discrepancy in the operating parameters of the equipment.

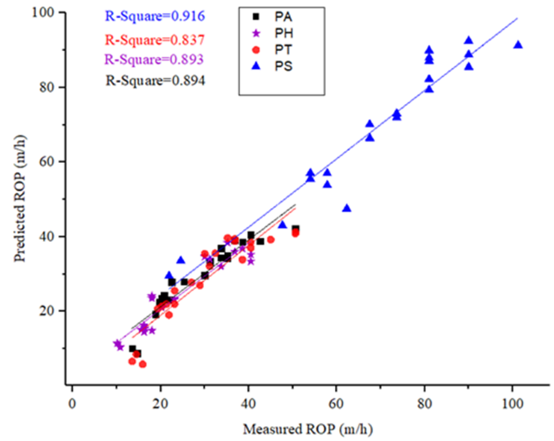
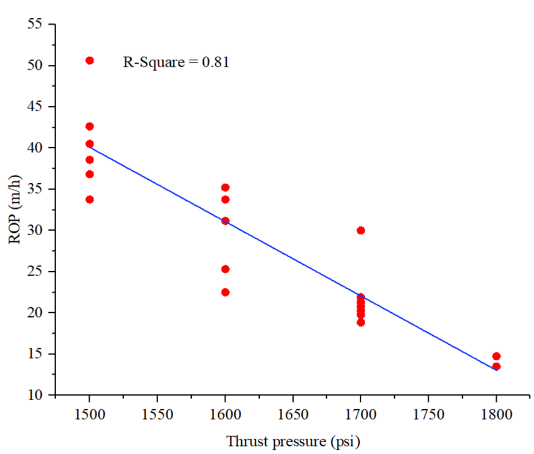


Figure 6. Predicted and measured values of ROP (m/h) in multivariate regression analysis of Atlas Copco ROC L8 (PA), Husherr (PH), Tamrock-1500 (PT), and Sunward-SWDE200 (PS)

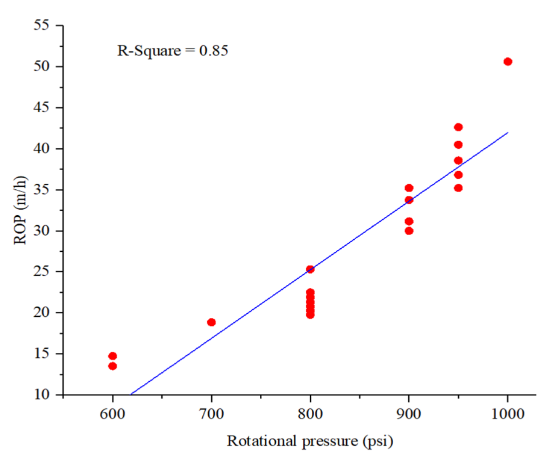
$$ROP = 122.158 - 0.019\ ThP - 0.014RP - 0.62MRMR - 0.445Sch \quad (8)$$

In studied drilling machines, thrust pressure demonstrated the high correlation with rate of penetration across all studied cases, with the exception of the Tamrock-1500, where mining rock mass rating emerged as the most influential parameter. Generally, as thrust pressure increases, ROP tends to rise as well; however, this relationship is influenced by factors such as rotary speed, rock properties, and drilling conditions. As the statistical analysis progressed, it was found that ROP decreases with increasing thrust pressure in the present study. Research into the cause of this phenomenon highlights both high and low strength rock. The relations between rate of penetration of all considered drilling machines and thrust pressure, rotational pressure (considering UCS), MRMR, and Schmidt Hammer Rebound are illustrated in Figures 7 - 10. According to these figures, the relationship between rotational pressure and ROP indicated that this parameter generally increases with higher rotary speeds. An increase in RP corresponds with a rise in ROP, provided the ground conditions remain constant. The operator cited the need to prevent excessive bit wear as the reason for reducing RP in hard rock conditions.

Furthermore, MRMR and Schmidt hammer rebound hardness inversely correlated with ROP, as elevated geomechanical competency (high MRMR or SH) amplified specific energy requirements for rock fragmentation. This relationship underscores the dominance of intact rock strength and joint density in dictating drillability.

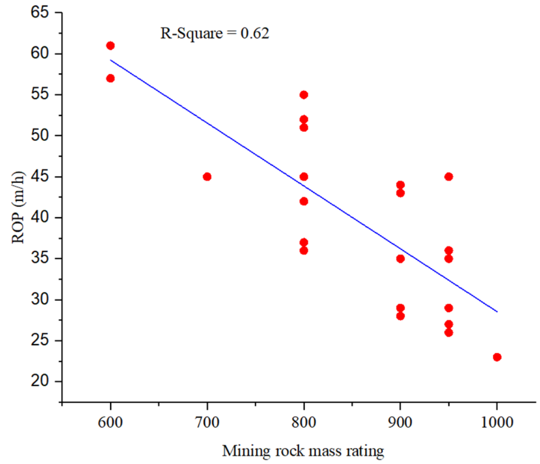


(a) ROP and Thrust pressure

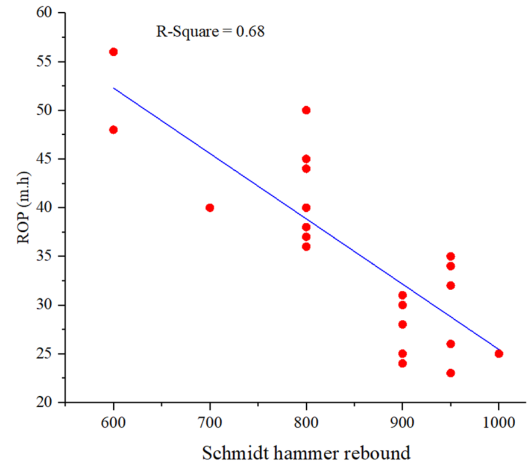


(b) ROP and Rotational pressure

Figure 7. Relation between ROP of Atlas Copco machine and Thrust pressure, Rotational pressure, Mining rock mass rating, and Schmidt hammer rebound

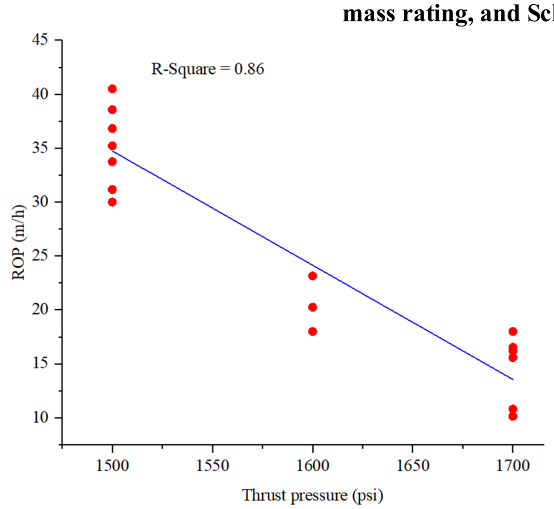


(c) ROP and Mining rock mass rating

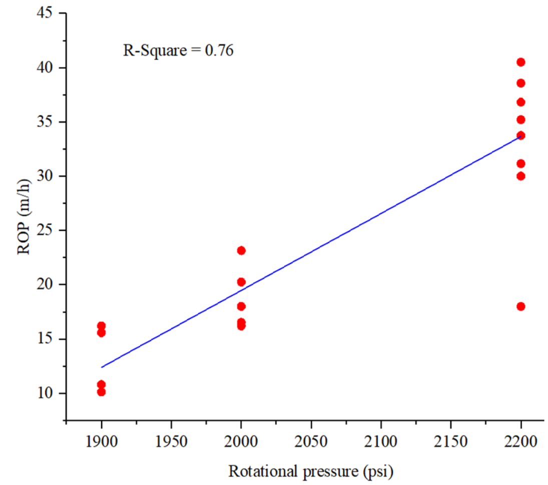


(d) ROP and Schmidt hammer rebound

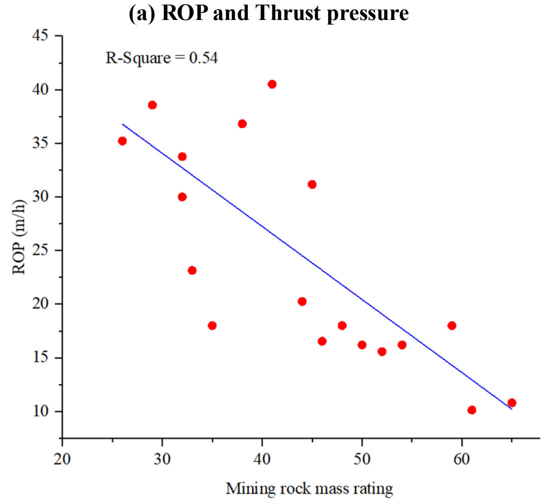
Figure 7. Relation between ROP of Atlas Copco machine and Thrust pressure, Rotational pressure, Mining rock mass rating, and Schmidt hammer rebound



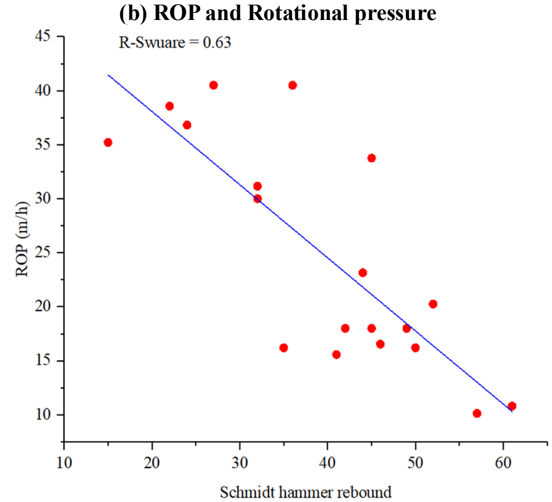
(a) ROP and Thrust pressure



(b) ROP and Rotational pressure

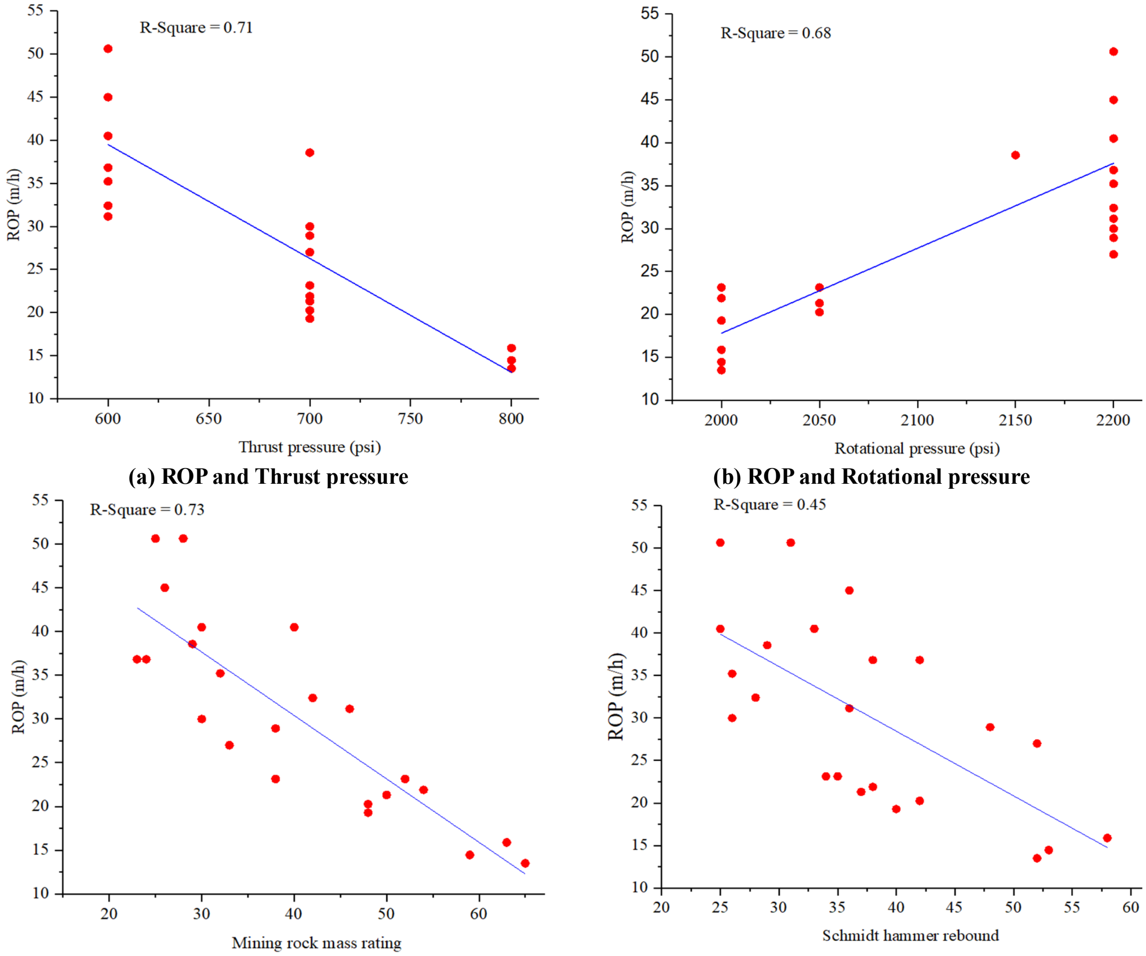


(c) ROP and Mining rock mass rating



(d) ROP and Schmidt hammer rebound

Figure 8. Relation between ROP of Husher machine and Thrust pressure, Rotational pressure, Mining rock mass rating, and Schmidt hammer rebound



(a) ROP and Thrust pressure **(b) ROP and Rotational pressure**

(c) ROP and Mining rock mass rating **(d) ROP and Schmidt hammer rebound**

Figure 9. Relation between ROP of Tamrock machine and Thrust pressure, Rotational pressure, Mining rock mass rating, and Schmidt hammer rebound

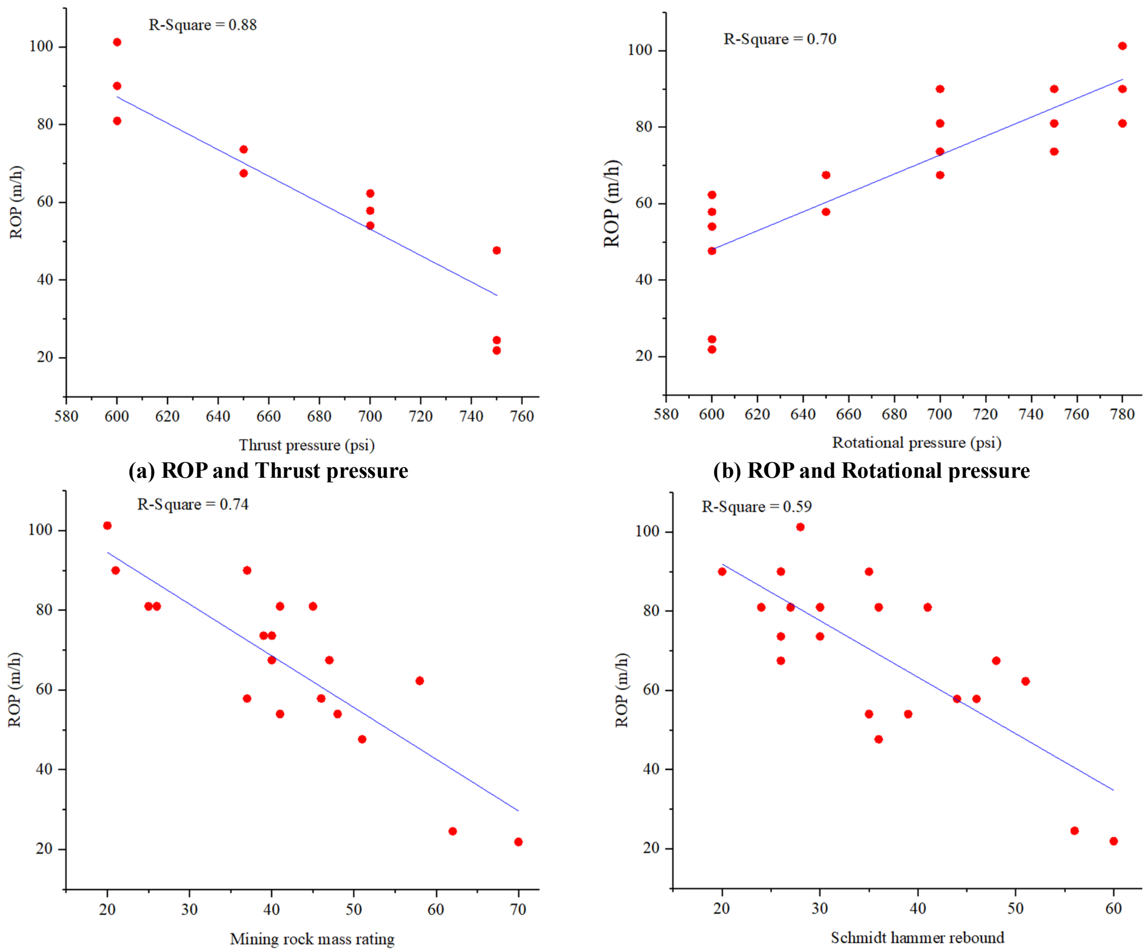
Multivariate regression models failed to achieve the desired predictive accuracy due to heterogeneity in thrust pressure and rotational pressure responses across drilling rigs operating in rock masses of variable strength (low to high UCS). To address this limitation, ANN-based predictive models were implemented. Python, a programming language widely adopted in machine learning (ML) workflows, was selected for its extensive ecosystem of scientific libraries, including:

NumPy: Facilitates efficient computation on multidimensional arrays and matrices, enabling high-performance linear algebra operations.

Pandas: Provides data structures (e.g., DataFrames) for preprocessing, cleaning, and feature engineering of drilling datasets.

Matplotlib: Generates publication-quality visualizations (e.g., ROP vs. thrust pressure scatterplots, loss curves) for exploratory data analysis and model diagnostics.

The number of neurons in hidden layers is a critical hyperparameter in ANN design, directly influencing predictive accuracy and computational efficiency. In this study, iterative experimentation was conducted to identify optimal neuron configurations for modeling rate of penetration in heterogeneous rock masses. Insufficient neurons can impede the network's capacity to address complex problems and generate accurate estimations. Conversely, employing a larger number of neurons can make the network more accessible to a broader statistical community. However, this strategy requires training more individuals and demands greater processing power, which can result in overfitting and increased time consumption. Therefore, it is possible to effectively train the network and attain satisfactory results by utilizing an appropriate number of intermediate neurons [33].



(c) ROP and Mining rock mass rating **(d) ROP and Schmidt hammer rebound**

Figure 10. Relation between ROP of Sunward machine and Thrust pressure, Rotational pressure, Mining rock mass rating, and Schmidt hammer rebound

In this study first-order gradient-based optimizers were integrated with the backpropagation algorithm to iteratively update synaptic weights and minimize the loss function. In this framework, backpropagation computes the gradient of the loss function with respect to each network parameter, enabling error signal propagation from the output layer backward through hidden layers. Moreover, optimization algorithms adjust parameters using these gradients to converge toward a local minimum of the loss landscape.

The following algorithms were employed to balance computational efficiency and convergence stability in ROP prediction:

- Gradient descent (GD) optimization algorithm;
- Stochastic gradient descent (SGD) optimization algorithm;
- The adaptive gradient method (ADAGRAD); and
- The Adaptive Moment Estimation Method (ADAM)

Table 3 summarizes the evaluated artificial neural network architectures, optimization algorithms, and corresponding performance metrics based on the coefficient of determination (R^2) for rate of penetration prediction. The mean squared error loss function was employed to quantify discrepancies between predicted and observed ROP values across networks with one and two hidden layers.

Table 3. The best attained networks with Different Architectures and Accuracy Results

No	Architecture	Hidden1 activation	Hidden2 activation	Output activation	Optimizer	Train R^2	Test R^2
1	mlp-4-20-16-1	Selu	Selu	Linear	GD	92	91
2	mlp-4-20-16-1	Selu	Selu	Linear	SGD	94	93
3	mlp-4-20-16-1	Selu	Selu	Linear	Adagrad	80	77
4	mlp-4-20-16-1	Selu	Selu	Linear	Adam	97	96
5	mlp-4-5-3-1	Elu	Selu	Linear	GD	68	81
6	mlp-4-5-3-1	Elu	Selu	Linear	SGD	89	77
7	mlp-4-5-3-1	Elu	Selu	Linear	Adagrad	27	11
8	mlp-4-5-3-1	Elu	Selu	Linear	Adam	92	87
9	mlp-4-12-10-1	Relu	Tanh	Linear	GD	84	70
10	mlp-4-12-10-1	Relu	Tanh	Linear	SGD	90	85
11	mlp-4-12-10-1	Relu	Tanh	Linear	Adagrad	2	0
12	mlp-4-12-10-1	Relu	Tanh	Linear	Adam	96	87
13	mlp-4-12-10-1	Exponential	Tanh	Relu	GD	84	80
14	mlp-4-12-10-1	Exponential	Tanh	Relu	SGD	91	86
15	mlp-4-12-10-1	Exponential	Tanh	Relu	Adam	95	92

The results in Table 3, which compare neural network architectures and optimization algorithms, reveal that Adagrad-based methods exhibit suboptimal performance in predicting the Rate of Penetration (ROP) in heterogeneous rock masses. Adagrad's diminishing learning rates, coupled with its inability to adapt to sparse geomechanical datasets, resulted in poor convergence ($R^2 < 0.75$) and failed to address the nonlinear interactions between drilling parameters and ROP. In contrast, Adam, Stochastic gradient descent, and Gradient descent algorithms demonstrated robust predictive accuracy. Among these, the Adam optimizer achieved the highest performance, with a 4-20-16-1 architecture (4 inputs, 20 and 16 neurons in hidden layers, 1 output) yielding an R^2 of 0.96 on testing data. Adam's adaptive learning rates and momentum integration enabled rapid convergence (<1000 epochs) and precise minimization of the loss function during training, as evidenced by the steep error reduction in Figures 11 and 12.

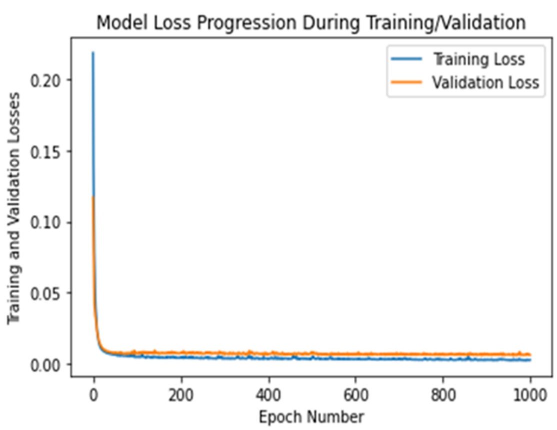


Figure 11. Convergence chart for training data of Adam's method

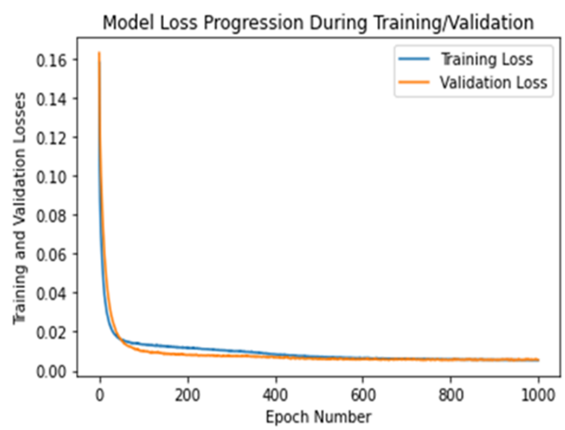


Figure 12. Data convergence chart for testing Adam's method

Figures 13, 14, and 15 illustrate the correlation between predicted ROP values derived from the optimized artificial neural network models (using Gradient descent, Stochastic gradient descent, and Adam optimization algorithms) and measured ROP values from field observations. These scatterplots highlight the predictive accuracy of each algorithm, with Adam (Figure 15) demonstrating the strongest alignment ($R^2 = 0.96$) between model outputs and ground-truth data.

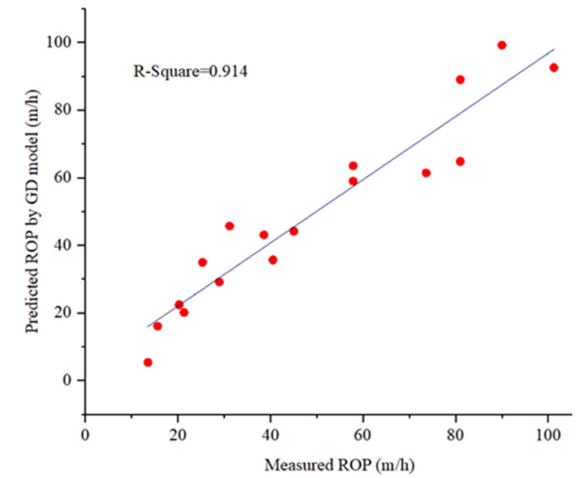


Figure 13. Comparing predicted and measured ROP by the GD model

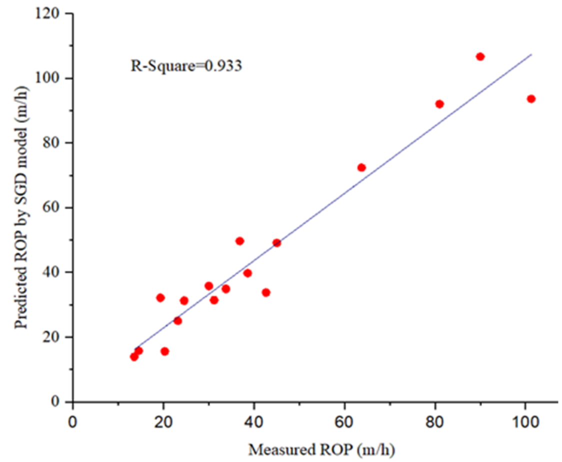


Figure 14. Comparing predicted and measured ROP by the SGD model

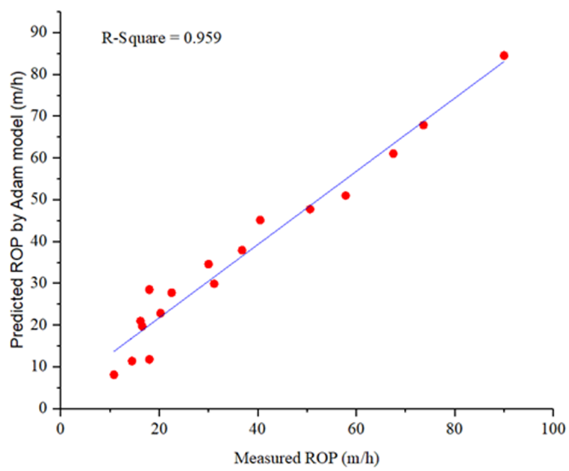


Figure 15. Comparing predicted and measured ROP by the Adam model

6. Network performance evaluation methods

Several methods have been proposed to assess the performance of neural networks. Each method evaluates and analyzes a specific measure of the network's performance. For example, some of these methods calculate the error in estimated values compared to actual values, as forecasting models emphasize the accuracy of the model. Table 4 compares the applied models based on the evaluation criteria considered in present study.

6.1. Coefficient of Determination (R^2)

R^2 indicates the degree to which the model's outputs align with the actual values and the extent of data dispersion (Equation 9):

$$R^2 = 1\text{-}\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{n}(y_i-\bar{y}_i)^2} \quad (9)$$

Where $\hat{y}_i$, y_i, and $\bar{y}$ represent the estimated value, the real value, and the average value of the i sample, respectively [68].

6.2. Root mean square error (RMSE)

RMSE represents the square root of the difference of the average square root of the error (Equation 10) [68].

$$RMSE = \sqrt{\frac{\sum(y_i - \hat{y}_i)^2}{N}} \quad (10)$$

6.3. Mean Absolute Error (MAE)

MAE calculates the mean absolute value of the error difference between the actual value and the calculated value using Equation (11) [68].

$$MAE = \frac{\sum|y_i - \hat{y}_i|}{N} \quad (11)$$

Table 4. Comparison of the best ANN based on various criteria

	Algorithm	R^2 Training	R^2 Test	RMSE Train	MAE Train	RMSE Test	MAE Test
ANN	GD	92%	91%	7.449	5.738	8.006	6.332
ANN	SGD	94%	93%	7.237	5.673	7.919	6.244
ANN	Adam	97%	96%	5.495	4.359	4.296	4.551

7. Sensitivity Analysis

Sensitivity analysis constitutes a critical component of predictive modeling, enabling the quantification of a model's responsiveness to variations in input parameters relative to target outputs. This analysis was conducted using Equation (12). A higher relevancy factor (r) signifies a stronger association between an input parameter (e.g., Thrust pressure, MRMR) and the target variable (ROP), reflecting its greater relative influence on model predictions. Application of this technique to the neural network and operational dataset confirms that all evaluated parameters exert statistically significant effects on rate of penetration predictions (Figure 16). Notably, mining rock mass rating and thrust pressure demonstrated the highest and lowest sensitivity respectively.

$$r(P_i, Ave) = \frac{\sum_{i=1}^{n}(P_{l,i} - \bar{P}_l)(Ave_i - \overline{Ave})}{\sqrt{\sum_{i=1}^{n}(P_{l,i} - \bar{P}_l)^2 \sum_{i=1}^{n}(Ave_i - \overline{Ave})^2}} \tag{12}$$

Where $P_{l,i}$ and $\bar{P}_l$ are the ith and average values of the kth input parameter, respectively. Likewise, $Ave_i$and $\overline{Ave}$ signifies the ith real value and average value of the predicted ROP by ANN model respectively [69].

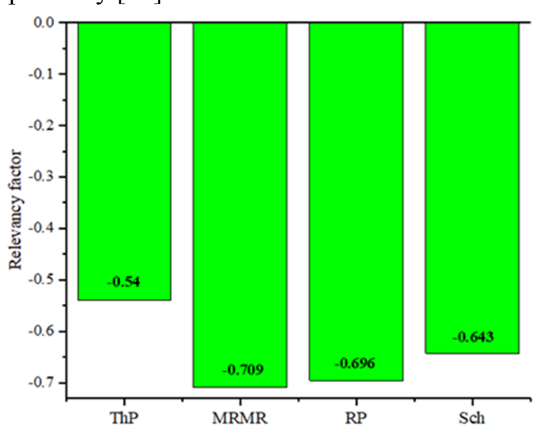


Figure 16. Input parameters' effect on ROP based on the designed ANN (ThP: Thrust pressure, MRMR: Mining rock mas rating, RP: Rotational pressure, Sch: Schmidt hammer rebound)

8. Conclusions

This study investigated the rate of penetration at the Sungun copper mine using field data from 85 blastholes drilled by four drilling machines: Atlas Copco ROC L8, Husherr, Sunward-SWDE200, and Tamrock-1500. A comprehensive database integrating field measurements (e.g., thrust pressure, rotational pressure) and laboratory-derived parameters (e.g., Schmidt hammer rebound hardness, MRMR) was compiled to assess correlations between geomechanical variables and ROP. Multivariate regression analysis yielded a coefficient of determination (R^2 = 0.74), confirming the insufficient accuracy in predicting the rate of penetration by considering mining rock rass rating, Schmidt hammer rebound, thrust pressure, and rotational pressure as effective and input parameters. Furthermore, Artificial neural network models were developed in Python, employing first-order optimization algorithms (Adam, SGD, GD, Adagrad). The Adam-optimized ANN (4-20-16-1 architecture) demonstrated superior performance, achieving R^2 = 0.97 (training) and R^2 = 0.96 (testing), with corresponding root mean square error values of 4.359 and 4.296, respectively.

Sensitivity analysis revealed that MRMR exhibited the highest influence on ROP, while thrust pressure exerted the least impact, underscoring the dominance of rock mass integrity over operational parameters in drillability.

9. Limitations and Future Recommendations

While the proposed framework provides accurate rate of penetration predictions, several limitations warrant attention:

- Constant Bit Diameter: The study assumed uniform drill bit diameters; future work should evaluate diameter variability's effect on ROP.
- Dataset Scope: The model was trained on 85 samples from a single porphyry copper deposit. Generalizability requires expansion to diverse lithologies and hybrid deep learning architectures.
- Field Validation: Integration of real-time sensor data could enhance model adaptability to dynamic drilling conditions.

Data availability

The data that support the findings of present study are available upon request.

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کاربرد روش‌های هوشمند در پیش‌بینی نرخ نفوذ مته‌های حفاری در معادن روباز

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اطلاعات مقاله

تاریخ ارسال: ۲۰۲۵/۰۳/۱۶
تاریخ داوری: ۲۰۲۵/۰۵/۲۱
تاریخ پذیرش: ۲۰۲۵/۰۶/۳۰

DOI: 10.22044/jme.2025.15933.3065

کلمات کلیدی

حفاری
نرخ نفوذ
روش‌های هوشمند
تخمین گشتاور تطبیقی
گرادیان نزولی تصادفی

چکیده

حفاری یکی از مهم‌ترین عملیات در معدنکاری روباز است و نرخ نفوذ مته‌های حفاری یک شاخص اساسی این عملیات می‌باشد. مقاله حاضر به نرخ نفوذ مته‌های حفاری بر اساس رده‌بندی توده سنگ معدن، فشار رانش (وزن روی مته)، فشار چرخشی و سختی چکش اشمیت می‌پردازد. برای دستیابی به این هدف، مجموعه‌ای از داده‌ها شامل عملیات حفاری ۸۵ چال انفجار از معدن مس سونگون در ایران تهیه و با استفاده از روش‌های آماری و هوشمند تجزیه و تحلیل صورت گرفت. در این مطالعه، از تحلیل رگرسیون چند متغیره و شبکه‌های عصبی مصنوعی توسعه‌یافته در پایتون، با استفاده از الگوریتم‌های بهینه‌سازی مانند گرادیان نزولی، گرادیان نزولی تصادفی و تخمین گشتاور تطبیقی، برای پیش‌بینی نرخ نفوذ مته‌های حفاری استفاده گردید. ضریب تعیین (R^2)، میانگین خطای مطلق (MAE) و جذر میانگین مربعات خطا (RMSE) به عنوان شاخص‌های عملکرد برای ارزیابی روش‌های به کار گرفته در نظر گرفته شدند. در این تحقیق، مدل مبتنی بر تخمین گشتاور تطبیقی (Adam) با مقادیر $R^2 = 0.96$، $MAE = 4.55$ و $RMSE = 4.30$ عملکرد بهتری در مقایسه با سایر مدل‌ها نشان داد. علاوه بر این، تحلیل حساسیت نشان داد که رده‌بندی توده سنگ معدن، تأثیرگذارترین عامل بر نرخ نفوذ است، در حالی که فشار رانش کمترین تأثیر را دارد.

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