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Research article

Estimating Penetration Rate of Excavation Machine Using Geotechnical Parameters and Neural Networks in Tabriz Metro

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Penetration rate

Abstract

In this study, the penetration rate of the excavation machine in Tabriz Metro Line 2 using geotechnical parameters and neural networks is estimated. For this purpose, through comprehensive analysis, including borehole drilling, field and laboratory tests, and consideration of similar projects, the geotechnical parameters for soil and rock layers have been determined. Preprocessing data techniques, such as normalization, have been applied to address challenges such as noise and bias in raw data. Also, neural networks with varying architectures were evaluated using mean square error and correlation coefficient as evaluation metrics. The architecture (1-12-8) of this research demonstrates superior performance with a mean square error of 1.630 and a correlation coefficient of 0.932. This shows a strong relationship between predicted and actual penetration rate values. The findings of this research highlight the effectiveness of neural networks in estimating the penetration rate. Accurate estimations of the non-linear penetration rate were achieved by employing a single-layer neural network with multiple neurons using appropriate transfer functions. Overall, this research contributes to the understanding of geotechnical considerations for urban train routes and demonstrates the accuracy of neural networks for penetration rate estimation. These insights have implications for the design and engineering of similar projects.

1. INTRODUCTION

One of the most critical elements in the excavation of tunnels excavated using a Tunnel Boring Machine (TBM) is the evaluation of its advancement rate and, consequently, the estimation of the penetration per revolution of the cutter head. Due to the complexity of the chip formation process under the cutter head disk tools, empirical formulations have been developed over time to estimate the penetration per revolution based on key rock and disk parameters. However, some of these formulations have proven difficult to use or only applicable within a limited range of applications. Additionally, many methods do not consider all the essential parameters that can influence the rock breakage mechanism when using disk tools [1].

There has been a continuous interest in expanding underground rail networks, and shielded tunnel boring machines are widely employed in urban environments for tunnel construction worldwide due to their fast, safe, and high-speed tunneling capabilities [2]. In recent decades, numerous researchers have developed empirical and theoretical models to predict TBM performance through factors such as penetration rate, advance rate, and the field penetration index (FPI) [3-5]. To estimate TBM performance parameters like penetration rate, advance rate, and FPI, many simple Artificial Intelligence (AI) techniques, such as artificial neural networks (ANN), particle swarm optimization (PSO), and others, have been employed [6-9]. Furthermore, in a continuous effort to leverage advanced technologies, researchers have enhanced the accuracy of the back-analysis procedure by integrating Machine Learning (ML) technology. ML technology, as a subset of AI, utilizes historical data to predict new output values and has become a powerful tool in geotechnical engineering. Many researchers have successfully applied ML technology in this field [10-12].

Machine learning and deep learning methods excel in solving complex mapping problems and have increasingly found successful applications in the engineering field [13-17]. Sindhwani et al. showed that UCS, BTS, RQD, J_s, and thrust have emerged as the most significant variables in their ANN analysis, with a normalized importance of more than 85%. Torque had a value of 60% [2]. Armaghani et al. studied three intelligent models, namely pre-developed ANN, hybrid PSO-ANN, and hybrid ICA-ANN, to estimate the advance rate of TBMs. A comparison with previously developed intelligent models for TBM performance prediction showed that the proposed PSO-ANN and ICA-ANN models have a high degree of accuracy and efficiency, making them suitable as new techniques for predicting TBM performance [18].

Ahmadi et al. (2013) used a hybrid imperialist competitive algorithm and an artificial neural network algorithm that effectively combines local searching. In comparing the introduced ICA-ANN model and other intelligent models (BP-ANN, GA-ANN, PSO-ANN, and fuzzy logic approaches), the ICA-ANN model performed better [19]. Armaghani et al. reviewed previous studies to select the most influential parameters for PR. They identified seven parameters, including RQD, UCS, RMR, BTS, WZ, TF, and RPM, as model inputs. Using all 1286 datasets, they developed three predictive models (ANN, PSO-ANN, and ICA-ANN) to predict the PR of the PSRWT tunnel. They also studied the application of several optimization techniques for estimating the TBM advance rate in granitic rocks [18,20,21]. Farrokh et al. analyzed the available data and indicated that a specific set of parameters, including tunnel diameter, UCS, RPM, and rock type, account for approximately half of the variation in PR and PRev. These analyses further indicate that UCS is the single most crucial rock parameter controlling PRev. The frequency and condition of jointing can also dominate TBM performance, especially on harder rocks. Further study of this phenomenon, including a quantitative representation of joint spacing and condition, may be necessary to improve model accuracy in harder rock units [22].

Wang et al. developed a hybrid model that combined QPSO and an ILF-ANN. Sixteen features, including tunneling parameters and rock mass classes, were used as inputs to the model. The control parameters, such as the cutter head rotation speed and penetration, were used as outputs. The results showed that the proposed method achieved effective optimization performance. However, the study did not consider the various weights of the penetration rate and the rock-breaking specific energy in the loss function of the ANN [23]. Hassan et al. used Multiple-Linear Regression (MLR) and Artificial Neural Networks (ANNWs) to develop a predictive model based on specific tunneling parameters. The aim was to evaluate the relative importance of system parameters based on their influence on model responses [24]. Mahdevari et al. found that ANN is a useful tool for predicting tunnel convergence. They developed a Multi-layer Perceptron (MLP) neural network with nine inputs for predicting tunnel convergence. The optimum ANN architecture consists of nine neurons in the input layer, two hidden layers with 35 and 28 neurons respectively, and one neuron in the output layer [25]. Mahdevari et al. used AI algorithms, specific Support Vector Machines (SVM), and Artificial Neural Networks (ANN), to predict ground conditions in a TBM-excavated tunnel and avoid undesirable events such as machine trapping. They focused on predicting tunnel convergence based on effective parameters [26]. Zhou et al. systematically verified and compared hybrid XGB-based optimization techniques for predicting TBM PR. They developed hybrid models by combining XGB with six intelligent optimization algorithms. The goal was to improve the accuracy and effectiveness of predicting TBM PR [27]. Koopialipoor et al. focused on predicting TBM PR by developing a new model based on the Group Method of Data Handling (GMDH) model. They investigated and utilized several effective parameters for TBM PR, including RQD, UCS, RMR, BTS, WZ, TF, and RPM. Using field observations and laboratory tests, they prepared a database with 209 datasets to estimate PR. The GMDH model showed higher accuracy and can be considered a new model in this field [28].

The research study focuses on estimating the penetration rate along Tabriz Metro Line 2 using neural networks and geotechnical parameters. This study contributes to our understanding of geotechnical considerations for urban train routes and highlights the accuracy of neural networks in estimating penetration rates. These insights have significant implications for the design and engineering of similar projects. It's always exciting to see how innovative approaches and technologies can improve our understanding and enhance the efficiency of construction processes.

2. ARTIFICIAL NEURAL NETWORKS

The purpose of artificial neural networks (ANNs) is to replicate the structure and functioning of the human brain. One of the primary and significant applications of ANNs is in the field of forecasting. In essence, an artificial neural network is comprised of interconnected neurons arranged in different layers. These neurons communicate and exchange information with each other. Artificial neurons act as basic units for processing information within the network, performing simple information-processing tasks.

2.1. Neural Network Architecture

One or more neurons together form a network layer. A network can consist of one or more layers. In **Fig. 1**, a single-layer network with input R and neuron S is shown.

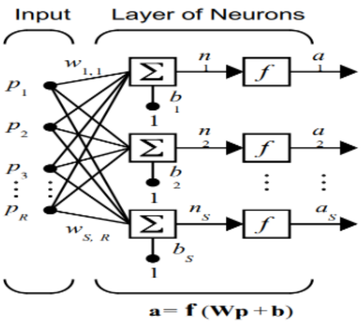


Fig. 1. A single-layer network [36].

In this network, the elements of the input vector p are applied to all neurons. They are then multiplied by the respective weights, added to the bias, and passed through a transfer function to obtain the output. The output of the network will be a vector. It's important to note that the number of inputs (R) does not necessarily need to be equal to the number of neurons (S). In a composite single-layer network, different transfer functions can be utilized within a single layer, allowing for more diverse processing capabilities. Here is the calculation given in Eq. (1) as follows:

$$W = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,R} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,R} \\ \vdots & \vdots & . & \vdots \\ w_{S,1} & w_{S,2} & \cdots & w_{S,R} \end{bmatrix} \quad (1)$$

Where are: W – weight matrix (will have a size of S×R), $W_{n,m}$ – weight corresponding to input n for neuron m [36].

2.2. Improving The Results

To improve the results obtained from the training procedure:

1. The network can be reinitialized and trained multiple times to explore different solutions.
2. Increasing the number of neurons in the hidden layer can improve the network's flexibility and optimization potential, but it should be done incrementally to avoid potential issues.
3. Using a larger training dataset enhances the network's generalization capabilities and improves efficiency when dealing with new data [36].

2.3. Data Training

In the batch training method, the weights and biases of a neural network are updated after applying all the members of the training set. The slopes calculated for each input are added together to determine the final updates for the weights and biases.

Within the context of exploratory techniques, the algorithms focus on the efficiency analysis of standard reduction algorithms. Fast post-propagation algorithms are employed, making use of standard numerical optimization techniques. This section examines three numerical optimization techniques:

1. Combined gradient: This technique encompasses functions such as trancgp, traincgf, traincgb, and trainscg.
2. Pseudo-Newton: This technique includes functions such as trainoss and trainbfg.
3. Levenberg-Marquardt: This technique employs the trainlm method.

These numerical optimization techniques are applied to improve the training process of the neural network. Each method utilizes different approaches to update the weights and biases, thereby enhancing the network's ability to learn and generalize from the training data. Table 1 shows some commonly used functions in various problems [36].

Table 1. Training functions [36]

Acronym	Algorithm	Description
LM	Levenberg-Marquardt	trainlm
BFG	BFGS Quasi-Newton	trainbfg
RP	Resilient Backpropagation	trainrp
SCG	Scaled Conjugate Gradient	trainscg
CGB	Conjugate Gradient with Powell/Beale Restarts	traincgb
CGF	Fletcher-Powell Conjugate Gradient	traincgf
CGP	Polak-Ribiére Conjugate Gradient	traincgp
OSS	One Step Secant	trainoss
GDX	Variable Learning Rate Backpropagation	traingdx

2.4. Determining The Number Of Neurons Among The Layers

To determine the appropriate number of neurons in the hidden layer, extensive research has been conducted, resulting in suggested values. These values serve to avoid relying solely on trial and error methods for finding the optimal number. Table 2 shows the various methods available for determining the number of neurons in the hidden layer. In this table, N_i represents the number of inputs, while N_0 represents the number of outputs in the model.

Table 2. Dimension calculation relationships between layers

Hecht-Nielse [29]	$\leq\ 2\ \times\ N_i\ +\ 1$
Ripley [30]	$\frac{N_i\ +\ N_o}{2}$
Paola [31]	$\frac{2 + N_o \times N_i + 0.5\ N_o \times (N_o^2 + N_i) - 3}{N_i\ +\ N_o}$
Wan [32]	$2\frac{N_i}{3}$
Masters [33]	$\sqrt{N_i\ \times\ N_o}$
Kaastra and Boyd Kanellopoulos and Wilkinson [34,35]	$2N_i$

2.5. Determining The Number Of Neurons Among The Layers

The gradient descent algorithm is generally known for being slow, as it requires a small learning rate to ensure stable learning. In contrast, the momentum method is often faster than the simple gradient descent method, as it allows for a higher learning rate while maintaining stability. However, even the momentum method can be too slow for certain problems. It tends to work well with incremental learning methods. For small and medium-sized networks with sufficient memory, the Levenberg-Marquardt learning function is commonly used. In cases where memory is limited, there are other faster algorithms available. In the case of larger networks, trainscg or trainrp can be employed.

Multi-layer networks possess the remarkable ability to perform both linear and non-linear calculations, making them well-suited for accurately estimating desired functions. These networks can even surpass the limitations of perceptrons. It's important to note that, in theory, once a network is trained, it should be capable of correctly performing the related operations. However, it should also be acknowledged that achieving the optimal solution is not guaranteed in every situation.

3. PROJECT INTRODUCTION

Tabriz Metro Line 2 is a key urban train route within the Tabriz metro system. This route spans approximately 22.4 km and comprises 22 stations. It originates from the Qaramelk and terminates at the Tabriz International Exhibition. Based on the studies conducted in this area, fine-grained alluvial and silty sediments have been observed. Among these fine-grained alluvial layers, there are also sandy deposits, but the tunnel route mostly passes through the fine-grained alluvial sediments.

3.1. Geotechnical Parameters Between Station S01 And Station S03

In this section, the geotechnical parameters for the design of soil and rock layers along the length of the route are presented. These parameters are determined based on observations made during borehole drilling, examination of field and laboratory test results, consideration of geotechnical studies conducted on projects similar to the scope of the current project, and engineering judgment. The division of the route from station S01 to station S03 is determined by factors such as the distance between boreholes, type of subsurface layers, underground water level, SPT numbers, and the variety of subsurface layers. You can find a summary of this division in Table 3. Additionally, Fig. 2 showcases the route investigated in this study, highlighted in red.

Table 3. Geotechnical parameters from station S01 to station S03 [37]

Mileage	04+550 ~ 05+050	04+100 ~ 04+550	03+350 ~ 04+100	02+550 ~ 03+350
Dominant type of soil	Alternation of coarse-grained (SM) and fine-grained alluvium (ML & CL)	Fine-grained alluvium (ML & CL)	Alternation of coarse-grained (SM) and fine-grained alluvium (ML & CL)	Alternation of coarse-grained (SM) and fine-grained (ML) alluvium
Specific dry weight (gr/cm^2)	1.70 ~ 1.80	1.65 ~ 1.75	1.75 ~ 1.80	1.70 ~ 1.80
Cohesion C (KPa)	300 ~ 400	150 ~ 250	300 ~ 500	200 ~ 350
Internal friction angle φ	25 ~ 27	26 ~ 28	26 ~ 28	30 ~ 32
Elastic modulus (MPa)	40 ~ 50	35 ~ 45	40 ~ 50	50 ~ 60
shear modulus (MPa)	15.0 ~ 19.0	13.0 ~ 17.0	15.0 ~ 19.0	19.0 ~ 22.5
Permeability coefficient (cm/s)	$10^{-6} \sim 10^{-5}$	$10^{-5} \sim 10^{-4}$	$10^{-5} \sim 10^{-4}$	$10^{-4} \sim 10^{-3}$

Fig. 2. The investigated route from line 2 of the city train.

4. DATA PREPROCESSING

Raw data often encounter challenges such as noise, bias, significant variations in dynamic range, and sampling. Utilizing raw data in its original form can weaken subsequent designs. In essence, data preprocessing encompasses all the transformations applied to raw data to make it more manageable and effective for subsequent processing, such as estimation. Various tools and methods exist for data preprocessing, with normalization being one notable example. This method involves converting the data into a new format with a different range or suitable distribution. Tables 4 and 5 provide the maximum, minimum, average, standard deviation, and variance values for each parameter. It's important to note that these values were obtained before normalization.

Table 4. Statistical values related to the investigated variables

	Descriptive Statistics					
	Minimum	Maximum	Average		standard deviation	Variance
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Torque (Mn. m)	1.10	5.30	4.1347	0.0137	0.3474	0.121
Trust force (KN)	7195.00	36265.00	22371.0200	186.8675	4734.7981	22418313.642
Speed $(\frac{\mathrm{mm}}{\mathrm{min}})$	5.00	55.00	33.3006	0.1884	4.7746	22.797
Friction angle (°)	5.04	28.48	15.5879	0.2291	5.8062	33.712
Cohesion (KPa)	11.19	58.93	41.3564	0.4494	11.3885	129.699
Special weight $(\frac{\mathrm{gr}}{\mathrm{cm}^3})$	1.82	1.97	1.8967	0.0017	0.045	0.002
Shear modulus $(\frac{\mathrm{kg}}{\mathrm{cm}^2})$	28.52	155.2	71.4264	1.0888	27.5891	761.159
Water table (m)	11.00	17.80	14.6639	0.0771	1.9554	3.824
Penetration rate $(\frac{\mathrm{mm}}{\mathrm{rot}})$	4.00	36.00	19.0961	0.1443	3.6576	13.378

Table 5: Statistical values related to the normalized variables studied

	Descriptive Statistics					
	Minimum	Maximum	Average		standard deviation	Variance
	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Torque $(Mn.m)$	0	1	0.7226	0.00327	0.08273	0.007
Trust force (KN)	0	1	0.5221	0.00643	0.16288	0.0027
Speed $(\frac{mm}{min})$	0	1	0.566	0.00977	0.09549	0.009
Friction angle (°)	0	1	0.45	0.00977	0.24763	0.061
Cohesion (KPa)	0	1	0.6319	0.00942	0.2386	0.057
Special weight $(\frac{gr}{cm^3})$	0	1	0.5271	0.01224	0.31009	0.096
Shear modulus $(\frac{kg}{cm^2})$	0	1	0.3387	0.0086	0.21780	0.047
Water table (m)	0	1	0.5388	0.01135	0.28756	0.083
Penetration rate $(\frac{mm}{rot})$	0	1	0.4718	0.00451	0.1143	0.013

5. THE RESULTS OF NEURAL NETWORKS

Matlab utilizes neural networks for clustering, estimation, and prediction of various problems. This method is categorized as a non-linear approach. In this particular study, the back-feed algorithm, a subset of the back-propagation algorithms, was employed. The newff command line function is utilized for this purpose. A single-layer neural network with multiple neurons is utilized to address the non-linear problem of penetration rate. The tansig transfer function is used for the intermediate layer, and the purlin function is used for the output layer.

The neural network consists of 8 inputs and 1 output. Normalization of the data is not required, and this step is handled by the mapminmax function. After the data pre-processing stage, it is time to train the network. In this modeling approach, 70% of the data is allocated for training, 15% for validation, and the remaining 15% for network testing. Once the training and forecasting phases have been completed for each of these partitions, the error function and the regression coefficient (or correlation coefficient) are calculated for each one. The selection of the best architecture is typically based on the lowest mean square error. Alternative error functions such as SSE and RMSE can also be utilized in neural networks. It is worth noting that after each execution, the existing network should be closed. Executing additional training sessions on the same network may lead to overfitting, compromising the reliability of the results. Before running the program, it is necessary to determine the number of neurons in each layer. To assist with this task, Table 2 can be consulted to calculate the number of intermediate layers, and the results can be recorded in Table 6.

Table 6. The number of neurons in each interlayer

$\le 2 \times N_i + 1$	≤ 17
$\frac{N_i + N_o}{2}$	*4.5*
$\frac{2 + N_o \times N_i + 0.5\, N_o \times (N_o^2 + N_i) - 3}{N_i + N_o}$	*1.2*
$2\frac{N_i}{3}$	*5.33*
$\sqrt{N_i \times N_o}$	*2.82*
$2N_i$	*16*

In order to assess the efficiency of each architecture, two parameters, namely mean square error and correlation coefficient, have been utilized. The selection of the best architecture is determined by the lowest value of the mean square error. It should be noted that alternative error functions can also be employed in neural networks, such as root mean square error or sum of squared differences. For this investigation, 14 models with varying numbers of interlayers were selected. As depicted in Table 7, the architecture (1-12-8) demonstrates the lowest error among the other models. This particular model exhibits a mean square error value of 1.630 and a coefficient of determination of 0.932. The mean square error is a significant factor in the selection of the optimal topology. The diagram in Figure 3 shows the predicted and actual values obtained from the device and the correlation between them. Fig. 4 shows the variation in penetration rate changes versus speed, thrust force and torque.

Among the geotechnical parameters, cohesion and friction angle play the most influential roles in the penetration rate within this system. An increase in both cohesion and friction angle leads to a significant reduction in the penetration rate. On the other hand, changes in soil density have a relatively negligible impact on the penetration rate. Thus, soil density is considered to have the least effect among the geotechnical parameters on the penetration rate (Fig. 5).

As the shear modulus increases, the penetration rate also increases, but this occurs with a relatively gradual decline. Furthermore, as the underground water parameter increases (specifically, the water height above the tunnel), the device becomes capable of penetrating deeper into the soil (Fig. 6).

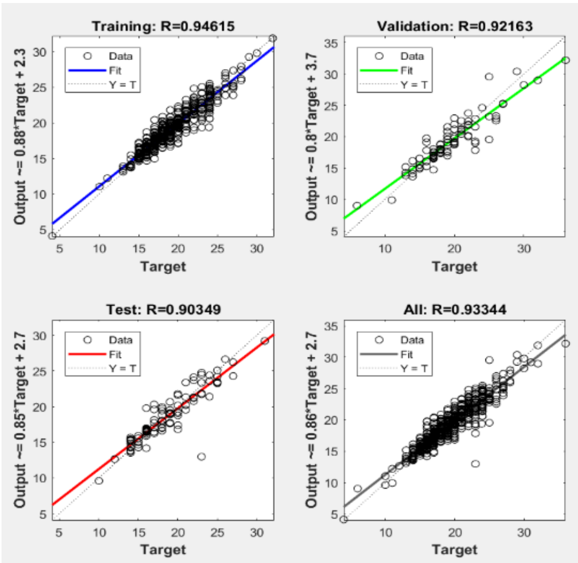
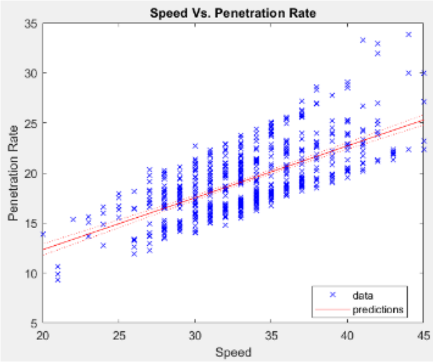


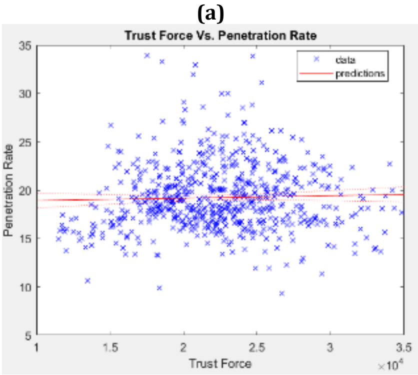
Fig. 3. Graph of correlation values for four modes of training, validation, test, and whole sample.

Table 7. The results obtained from different implemented models

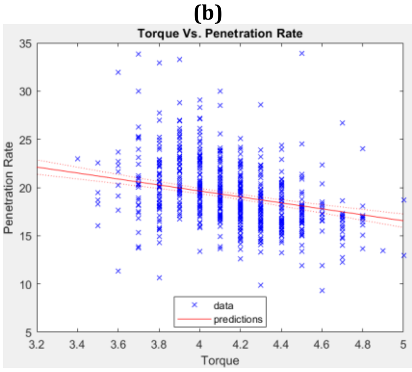
No.	Network architecture	R (Train)	R (Test)	R (All)	MSE
1	1-3-8	0.917	0.922	0.916	2.846
2	1-4-8	0.904	0.914	0.908	1.912
3	1-5-8	0.904	0.915	0.914	1.731
4	1-6-8	0.920	0.914	0.919	1.726
5	1-7-8	0.930	0.904	0.922	2.449
6	1-8-8	0.931	0.876	0.916	2.701
7	1-9-8	0.909	0.870	0.889	3.061
8	1-10-8	0.930	0.908	0.926	1.983
9	1-11-8	0.920	0.887	0.906	3.284
10	1-12-8	0.948	0.903	0.937	2.057
11	1-13-8	0.944	0.885	0.927	2.659
12	1-14-8	0.946	0.903	0.934	1.630
13	1-15-8	0.944	0.903	0.925	3.003
14	1-16-8	0.944	0.867	0.928	2.781



(a)



(b)



(c)

Fig. 4. (a): variation of torque with penetration rate; (b): Thrust force changes with penetration rate (c): velocity changes with penetration rate.

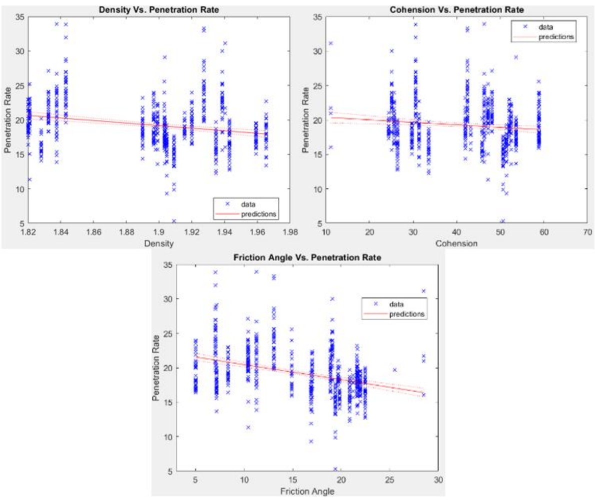


Fig. 5. Upper right: the amount of friction angle changes with penetration rate; Top left: the amount of adhesion changes with penetration rate; Bottom: rate of density changes with penetration rate

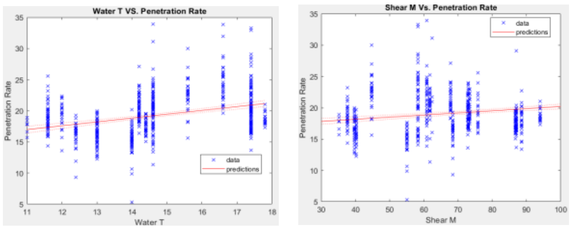


Fig. 6. Right: changes of shear modulus with penetration rate; Left: changes in water level with penetration rate.

6. CONCLUSIONS

The penetration rate is the most crucial factor in assessing the efficiency of a full-section excavation machine. For tunnel excavation in urban environments, generating the appropriate torque is one of the primary performance factors for the TBM (Tunnel Boring Machine) device. The torque force propels the TBM forward and rotates the cutter head. The device's torque is directly linked to the power it possesses in its gearbox. As the torque of the device increases, the penetration rate decreases. Thrust force, as a factor that affects torque and reduces speed, indirectly impacts the penetration rate's value.

To ensure the most accurate estimation of the penetration rate, this study utilizes state-of-the-art and intelligent computing methods. The examined parameters of the device include torque, thrust force, and rotation speed of the cutter head. Geotechnical parameters investigated consist of internal friction angle, adhesion, wet specific gravity, shear modulus, and stability level. Analyzing the results obtained from various methods reveals that among the machine parameters, speed has the most significant effect on the penetration rate. This effect is direct and positive, meaning that as the cutter head's rotation speed increases, the torque force decreases. Regarding geotechnical parameters, the underground water parameter exerts the most profound influence on the penetration rate. Increasing its value leads to higher penetration rates. Adhesion and internal friction angle have a crucial impact on reducing the penetration rate within this system. As the soil's specific gravity rises, the penetration rate marginally decreases. Therefore, specific gravity has the least impact among the geotechnical parameters on the penetration rate. As for the modulus of elasticity, an increase results in a gradual decrease in the penetration rate.

Out of the available methods, the neural network demonstrates the strongest ability to predict the penetration rate. Investigations indicate that among the machine parameters, speed holds the greatest influence, while thrust force possesses the least impact.

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