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)

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Abstract

One of the most widely used methods for the excavation of metro tunnels is mechanized excavation using an earth pressure balance (EPB) boring machine. Predicting the penetration rate of the boring machine can significantly reduce costs in mechanized excavation. Geological and geotechnical factors, machine specifications, and operational parameters can be influential on the penetration rate of the machine. Important geotechnical factors include cohesion, friction angle, and soil shear modulus. Among the important machine parameters, the thrust force of the jacks, the torque, and the rotational speed of the cutter head can be mentioned. In this study, after analyzing the main component, eliminating the outlier data, and normalizing the data, by considering the geotechnical factors and various parameters of the mechanized boring machine, the penetration rate of the EPB machine in the Tabriz metro line 2 tunnel has been predicted. For this purpose, linear regression methods, fuzzy logic using Mamdani and Sugeno algorithms, neuro-fuzzy method, and metaheuristic algorithms were used. To validate each model, statistical indices of the coefficient of determination (R^2), root mean squares error (RMSE), and performance indicator (VAF) were used. The results of the studies showed that the neuro-fuzzy method has a better prediction of the penetration rate in comparison to other methods. Also, the results of the sensitivity analysis revealed that the cutter head torque had the greatest effect on the penetration rate of the EPB machine.

1. INTRODUCTION

Nowadays, earth pressure balance (EPB) boring machines are widely used in soil environments, especially in urban areas, due to their high safety, reduction of tunnel displacement and convergence, as well as the rapid development of mechanical and electronic parts of the machine [1]. Tunneling with earth pressure balance (EPB) boring machines was first used in Japan in the 1970s [2]. Predicting the penetration rate of the machine is one of the most important problems in geotechnical engineering. Determining the penetration rate of the machine has a great effect on reducing excavation costs. In general, the parameters affecting the penetration rate include geological and geotechnical factors, machine specifications as well as operational parameters. Although the operating factors and specifications of the machine can be chosen by the designer, the geological and geotechnical conditions are relevant to the site [3-7]. When drilling with EPB machines, a large amount of energy is used to excavate into the soil and tunnel face support using the drilled soils. Therefore, when designing EPB tunneling machines, it is necessary to estimate the incoming loads and also, to predict the penetration rate of the machine [1]. Rotation speed and torque are the two main parameters in determining the penetration rate of the EPB machines' cutter head. The rotational speed during boring in homogeneous layers is considered constant, while the torque will change with changing the geological conditions. In the design phase of the machine, given the wide range of face soils, a suitable capacity for the cutter head torque should be considered [1, 8]. As the earth conditions become more complex, the design of earth pressure balance boring machines, as well as operating parameters, must be optimized [9]. In such circumstances, it is important to predict the penetration rate of the machine to design the project, predict the costs, and optimize the operational parameters [10].

Two geotechnical factors (supporting pressure and soil properties) and technological factors (machine design, thrust, and torque) are effective in the selection and advance of the EPB machine [8]. So far, many researchers have investigated the effect of different parameters on the penetration rate of earth pressure balance boring machines in soil environments. Chou et al. (2001), Zhao et al. (2006), Ball et al. (2009), Zumsteg et al. (2013), Alavi et al. (2014), and Zhao et al. (2018) studied soil conditions in excavation with EPB machines [11-16]. Centis and Giacomin (2004), on the other hand, studied the penetration rate of the earth pressure balance boring machines in some areas with high geological variations [17]. Carrieri et al. (2006) investigated the application of EPB machines in coarse-grained soils in Turin metro line 1 [18]. Song et al. (2010) and Shi et al. (2011) also presented a theoretical model for predicting the cutter head torque and thrust force in lands with soft soils [1, 19]. Song et al. (2010) calculated the torque required for excavation in clay and sand environments using radial shear velocity, amount of the cover material, cohesion, and soil pressure [19]. Shi et al. (2011) also showed that the friction between the cutting drill surfaces is the main factor affecting the cutter head torque, especially in complex geological conditions, using the physical modeling of the EPB machine [1]. Estimation of the penetration rate in EPB-TBM machines in mixed faces has been done by Toth and Zhao (2013) [20]. Barzegari et al. (2014) also studied the penetration rate of EPB machines in bouldery earth in Tabriz metro, providing suggestions to increase the penetration rate of the machine [21]. Namli and Bilgin (2017) also presented a model for predicting the advance rate of EPB machines in the complex geological conditions of Istanbul [22]. Avunduk and Copur (2018) also developed an experimental model for predicting the machine performance that was specific to the soil. Based on soil characteristics, including liquid limit, plastic limit, plasticity index, soil grain size, consistency index, and moisture content or percentage, they provided a model for predicting cutter head torque, thrust force, and field-specific energy [23]. Massinas et al. (2018) examined different aspects of EPB machine design in urban environments [24]. Faramarzi et al. (2020) also studied the parameters affecting the penetration rate of shield TBM in Tehran metro line 7. They investigated the effect of earth properties, cover material height, and linear and radial velocities on the cutter head torque and thrust, optimizing the machine penetration rate [8].

A review of the previous researches, shows that few studies have been conducted on the parameters affecting the penetration rate of the earth pressure balance boring machine in soil environments with complex geological conditions. In realistic models, both soil properties and machine characteristics must be considered to evaluate the penetration rate of the EPB machines. In addition, identifying land hazards is essential to select the appropriate strategy to improve soil conditions during excavation. If the excavating behavior of the earth is predicted in advance, there can be more confidence when deciding on the appropriate arrangements for determining the characteristics of the machine and optimizing the operational parameters. The main purpose of this study was, therefore, to investigate the effect of each of the geotechnical parameters and machine characteristics on the penetration rate of the earth pressure balance boring machines.

Tabriz Metro Line 2 project, as one of the major projects in the northwest of the country, has many complications and risks such as liquefaction, soil cohesion, groundwater problem, and underground cavities. In this study, by taking into account the geotechnical factors and various parameters of the EPB machine, the penetration rate (ROP: the rate of advance of the machine per rotation of the cutter head) of EPB machines in the Tabriz metro line 2 tunnel has been predicted. For this purpose, after analyzing the principal component, deleting the outlier data and normalizing the data using statistical methods, fuzzy logic (using Mamdani and Sugeno algorithms), neuro-fuzzy, as well as metaheuristic particle swarm optimization (PSO) algorithms, Genetic algorithm (GA), Whale Optimization Algorithm (WOA) and Ant Colony Algorithm (ACO), the effects of various geotechnical parameters and machine characteristics on the penetration rate of the earth pressure balance boring machine were studied.

2. THEORY OF FUZZY LOGIC

Fuzzy systems are rule-based expert systems that predict output according to the methods based on the principles of fuzzy logic, using specific inputs [25]. Fuzzy systems were first proposed in 1965 by Professor Lotfizadeh as a mathematical method for expressing the ambiguity of linguistic expressions; then they were developed in the 1970s with practical applications [26]. The language of fuzzy logic is based on if-then rules. Fuzzy algorithms, using precise mathematical analysis, can serve as an effective tool to describe the behavior of systems that are very complex or very poorly defined.

In classical sets, a member either belongs to the set or does not. Also, the boundaries of the classical set are well defined, but in the fuzzy sets, the boundaries are not clear and the extent to which members belong is relative. If μ is the degree of belonging or degree of membership, U is the universal set and x is a member of it, then the fuzzy set A in U is defined as a set of ordered pairs according to the relation 1:

$$A = \left\{ x \,.\, \mu(x) \middle| x \in U \right\} \quad (1)$$

where μ (x) is the membership function of the set A. The range of changes in μ (x) is between [0,1], such that zero means no membership and one means absolute membership in the fuzzy set. The numbers between these two values mean the degree of membership in the corresponding fuzzy set [27-29].

The fuzzy clustering method has many applications in various clustering problems. The purpose of this algorithm is to segment data into C clusters based on minimizing the least distance function according to relation 2:

$$J_m(U,V) = \sum_{k=1}^{n}\sum_{i=1}^{c} U_{ik}^{m} \|x_k - v_i\|^p \quad (2)$$

m is a fuzzy parameter that has a value greater than one. Also, v_i is the center of the i_{th} cluster. The variable $U_{ik} \in [0,1]$ is the degree of data belonging to each cluster, p is the degree of the Euclidean power, n is the number of input data and c is the number of clusters. In order to optimize the J_m (U, V) function, the optimization algorithm is performed in two steps of estimating U and V. The method is such that the centers of the clusters in the r step are calculated according to the value of U in the r-1 step using the equation 3:

$$v_i = \frac{\sum_{k=1}^{n} (U_{ik})^m \, x_k}{\sum_{k=1}^{n} (U_{ik})^m} \quad (3)$$

Then, the new value of U can be obtained using the equation 4 [29]:

$$U_{ik} = \sum_{j=1}^{c} \left(\frac{\|x_k - v_i\|}{\|x_k - v_j\|}\right)^{-2/(m-1)} \quad (4)$$

One of the most important fuzzy inference algorithms used in geology and geomechanics is Mamdani and Takagi Sugeno fuzzy inference algorithms. Mamdani fuzzy inference system has high expressive power and can implement multiple inputs and outputs simultaneously. In the Mamdani fuzzy inference algorithm, logical results are expressed with a relatively simple structure; it is mostly used in decision support systems. Takagi-Sugeno fuzzy inference algorithm was proposed by Sugeno to develop a systematic process for generating fuzzy rules. The Takagi-Sugeno fuzzy inference system is more commonly used in control systems. The output of the Sugeno algorithm uses a first-order polynomial in input variables as the result of the rule; the non-fuzzy method is usually of the weighted average and total weight methods [30].

In most cases, rock masses show anisotropic, nonlinear, and asymmetric behavior. Specifically, under these conditions, it is very difficult to model the machine penetration rate using a purely mathematical model. Under these conditions, neuro-fuzzy modeling can be used, which is a combination of fuzzy logic and neural networks. This model consists of two main components: the logical component and the numerical component. The logic component includes fuzzy sets, fuzzy logic, and approximate reasoning. The numerical component includes neural networks, data classification, and information analysis.

3. INTRODUCING TABRIZ CITY METRO LINE 2 PROJECT

Line 2 of the Tabriz metro, with a length of 22.4 km, including 22 stations, connects the eastern part of Tabriz to its west. Excavation of this project is done using a full-face boring machine. The outer diameter of the Tabriz metro line 2 tunnel is 9.49 meters, its inner diameter is 8.48 meters, the thickness of the segment is 35 cm and the thickness of the injection area is 15.5 cm. In the study area, the depth of the tunnel varies from 15 to 28 meters [31-32]. The geotechnical parameters of different soil and rock layers for the path length are presented in Table 1. Also, the mechanical properties of the EPB machine and the specifications of the concrete cover are described in Tables 2 and 3. Figure 1 shows the machine used in line 2 of the Tabriz metro.

Table 1. Geotechnical parameters of different layers in the path of Tabriz metro line 2 [31]

Chainage	2+550 ~ 3+350	3+350 ~ 4+100	4+100 ~ 4+550	4+550 ~ 5+050
Major material	Alteration of coarse-grained (SM) and fine-grained (ML) deposits	Alteration of coarse-grained (SM) and fine-grained deposit (ML & CL)	fine-grained deposit (ML & CL)	Alteration of coarse-grained (SM) and fine-grained (ML & CL)
Specific dry weight (gr/cm^3)	1.70 ~ 1.80	1.75 ~ 1.80	1.65 ~ 1.75	1.70 ~ 1.80
Cohesion (KPa)	200 ~ 350	300 ~ 500	150 ~ 250	300 ~ 400
Friction angle(◦)	30 ~ 32	26 ~ 28	26 ~ 28	25 ~ 27
Elastic modulus (MPa)	50 ~ 60	40 ~ 50	35 ~ 45	40 ~ 50
Shear modulus $(kg/cm2)$	80 ~ 140	30 ~ 90	25 ~ 80	20 ~ 60
Permeability coefficient (cm/s)	10^{-4} ~ 10^{-3}	10^{-5} ~ 10^{-4}	10^{-5} ~ 10^{-4}	10^{-6} ~ 10^{-5}

Table 2. Mechanical properties of the machine [31]

EPB				
Machine full length (m)	**Support system weight (ton)**	**Shield weight (ton)**	**Drilling diameter (m)**	**Machine length (m)**
86	350	625	9.49	9

Table 3. Specification of the concrete cover [31]

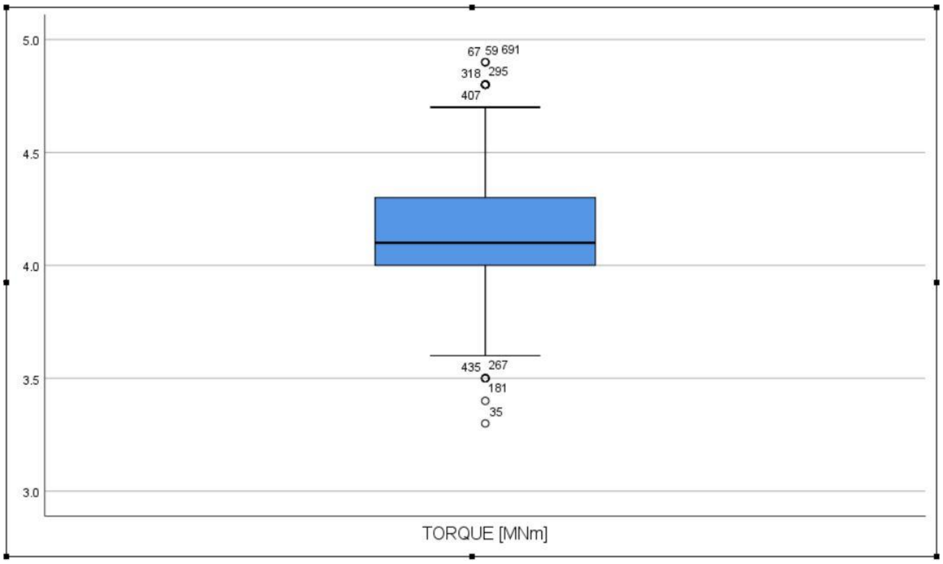
Segment specifications				
Width (m)	**Thickness (cm)**	**Internal diameter (m)**	**Outer diameter (m)**	**Number of segments**
1.5	35	8.48	9.18	1+1+7

Figure 1. EPB machine used in the Tabriz city metro line 2 project [31]

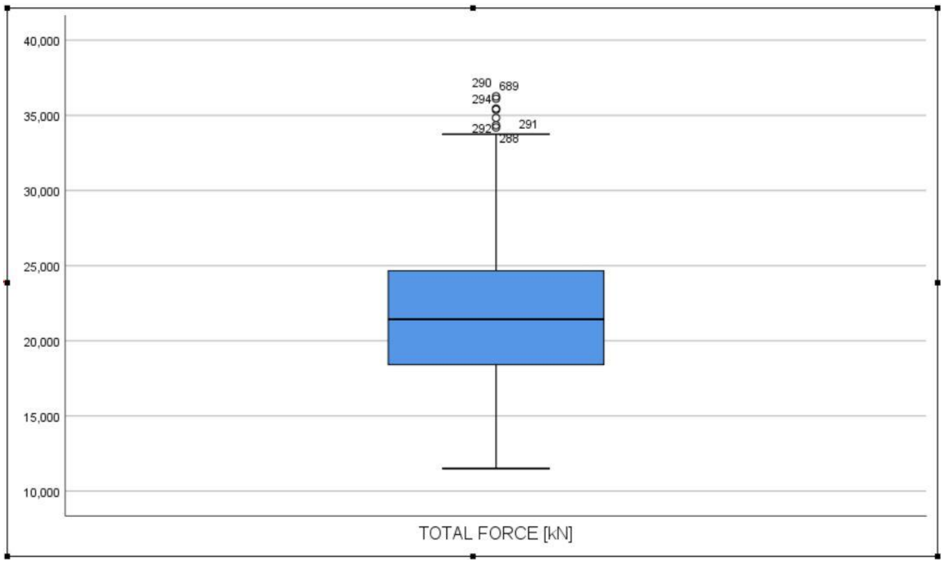
3.1. Pre-processing and normalization of data

Preliminary raw data were collected using a data logger in the tunnel route of Tabriz metro line 2. These data included torque, thrust force, velocity (machine progress per minute), rotation (number of cutter head rotations per minute), shear modulus, cohesion, friction angle, and machine penetration rate (machine advance per rotation of the cutter head). Raw data usually have problems such as noise, bias, and drastic changes in the dynamic range and sampling, and using them will undermine the subsequent designs. Therefore, it is necessary to convert the data into appropriate ones for injection into data mining algorithms. Data preprocessing includes all conversions that are done on raw data, making them easier and more efficient for subsequent processing. There are various tools and methods for preprocessing, such as the normalization method. Also, the factors affecting the output parameter do not have the same value. Some of these factors are more important in determining the output parameters, while some others have a slight effect on the desired output. In this case, the data reduction process is performed. One of the most widely used methods in the data reduction process is the principal component analysis method. In this study, the factors affecting the output parameter, following the analysis of the principal component, because they cover more than 95% of the changes, are torque, thrust force, velocity, rotation, shear modulus, cohesion, and friction angle.

A box plot was used to show the outlier data. For example, a box plot of the machine torque and thrust distribution is shown in Figure 2. The statistical properties of the data, after deleting the outlier data and before normalization, are shown in Table 4. After deleting the outlier data, the data were normalized. Figure 3 shows a graph of the normal distribution of torque and thrust force of the machine after deleting the outlier data. Also, Table 5 shows the statistical characteristics of the data after normalization.



(a)



(b)

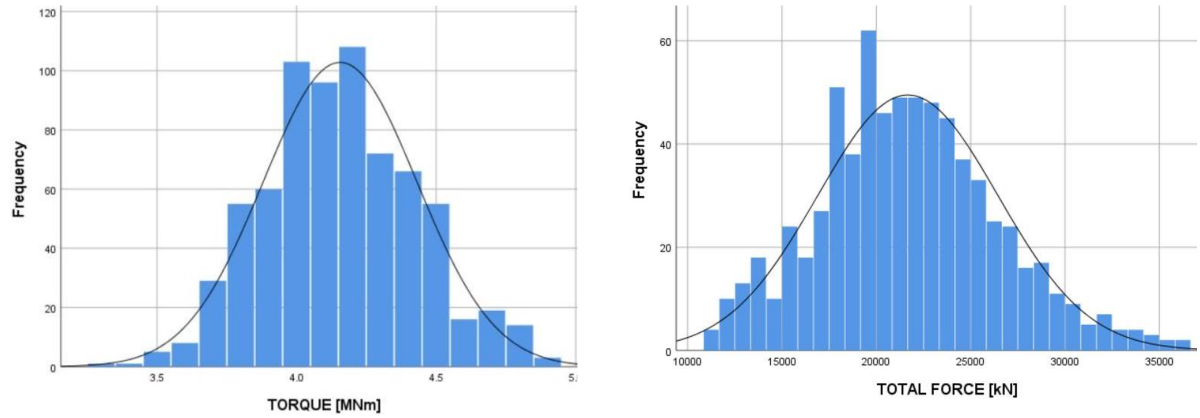
Figure 2. The box plot for eliminating the outlier data (a) torque and (b) machine thrust force

Table 4. Statistical characteristics of data after deleting the outlier data and before normalization machine speed: the advance rate of the machine per minute. Rotation: The number of cutter head rotations per minute.

	Minimum	Maximum	Mean	Standard deviation	Variance
Toque (MN.m)	3.30	4.90	4.16	0.28	0.08
Thrust force (MN)	11.51	36.26	21.67	4.77	22.80
Velocity(mm/min)	19	48	33.08	4.57	20.87
Rotation (rpm)	1.20	2.10	1.79	0.21	0.05
Shear modulus (kg/cm2)	35.24	114.44	68.94	19.38	375.55
Cohesion (kpa)	11.19	58.93	40.76	12.20	148.91
Friction angle (◦)	5.04	28.48	16.40	5.40	29.19

Table 5. Statistical characteristics of data after normalization

	Minimum	Maximum	Mean	Standard deviation	Variance
Torque (MN.m)	0.00	1.00	0.53	0.17	0.03
Thrust force (KN)	0.00	1.00	0.41	0.19	0.04
Velocity (mm/min)	0.00	1.00	0.49	0.16	0.02
Rotation (rpm)	0.00	1.00	0.65	0.24	0.05
Shear module (kg/cm2)	0.00	1.00	0.43	0.24	0.06
Cohesion (kpa)	0.00	1.00	0.62	0.25	0.06
Friction angle (◦)	0.00	1.00	0.48	0.23	0.05



(a) (b)

Figure 3. Normal distribution graph (a) torque and (b) the thrust force of the machine after deleting the outlier data

4. PREDICTING EPB MACHINE PENETRATION RATE USING LINEAR REGRESSION

After principal component analysis, elimination of the outlier data, and normalization of data, the relationship between each independent variable and ROP was investigated. In this step, linear, logarithmic, power, and exponential functions were used. The coefficients of determination (R^2) were evaluated using simple regression analyses of this step, as summarized in Table 6. The P-value of each independent variable was less than 0.05, so the models were valid at a 95% confidence level. Correlation analysis of ROP and independent variables showed that the highest correlation was between the penetration rate and the torque of the machine. Then, linear regression analysis was used to predict the penetration rate of the EPB machine in line 2 of Tabriz metro. The statistical results of the linear regression model are presented in Table 7. The Sig. statistic indicates the level of significance of the statistic F; if it is less than 0.05, it means that the change shown by the model is not due to chance, thereby confirming its accuracy. Also, the value of F obtained from statistical analyses (2513.30) was greater than that of F in the table (2.03). In addition, the absolute value of t is a coefficient greater than t in the table, so the model was valid at the 95% confidence level. Equation 5 shows the model obtained from the linear regression analysis.

$$\mathrm{ROP} = 19.671 + 0.128\ \mathrm{Torque} + 7.818 \times 10^{-4}\ \mathrm{Trust} + 0.564\ \mathrm{Speed} - 11.213\ \mathrm{Rotation} - 0.004\ \mathrm{G} + 0.005\ \mathrm{C} + 0.006\ \varphi \qquad R^2 = 0.916 \tag{5}$$

where ROP: penetration rate (the progress of the machine per one rotation of the cutter head (mm/rot.), Torque (MN.m), Trust (MN), Speed (mm/min), Rotation (rpm), G: shear modulus (Kg/cm2), C: cohesion (KPa) and φ: friction angle (degree). To validate the linear regression model, some other statistical indices, such as root mean square error (RMSE) and performance indicator (VAF), are calculated, using the relations 6 and 7 between the predicted values (t_i) and the measured ones (o_i):

$$\mathrm{VAF} = \left(1 - \frac{\left(\mathrm{var}(o_i - t_i)\right)}{\mathrm{var}(o_i)}\right) * 100 \quad (6)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{I=1}^{N}|o_i - t_i|} \quad (7)$$

Table 6. Correlation analysis of ROP and independent variables

	Linear	Logarithmic	Power	Exponential
Torque	0.48	0.45	0.46	0.44
Trust	0.36	0.34	0.37	0.36
Speed	0.38	0.35	0.36	0.35
Rotation	0.41	0.40	0.41	0.38
G	0.26	0.27	0.25	0.24
C	0.22	0.19	0.20	0.18
φ	0.18	0.17	0.17	0.16

Table 7. The statistical results of the linear regression

Independent variables	coefficient	Standard error	Sig.	R	R^2	t Value	Tabulated t	F Value	Tabulated F
constant	19.67	0.574	0.452	0.957	0.916	34.294	1.970 ±	2513.30	2.03
Torque	0.13	0.069	0.045			1.997			
Trust	7.82×10^{-4}	0.000	0.033			-5.302			
Speed	0.56	0.006	0.000			96.525			
Rotation	-11.21	0.163	0.000			-68.927			
G	-0.004	0.001	0.002			-3.167			
C	0.005	0.002	0.009			2.152			
φ	0.006	0.002	0.021			2.421			

The different performance indicators of linear regression analysis are presented in Table 8. The best prediction models have a coefficient of determination of 1, a performance indicator of 100, and a root mean square error of zero. The normal histogram diagram related to the proposed model of the linear regression method is shown in Figure 4. The P-P diagram of the linear regression model (Figure 5) is close to the straight line and its distribution is normal. The correlation between the actual values and the predicted values of the linear regression model is shown in Figures 6 and 7.

Table 8. The results of the linear regression model in the Tabriz metro line 2 tunnel

Model	Number of data	R^2	RMSE	VAF
Linear regression	711	0.916	0.791	91.55

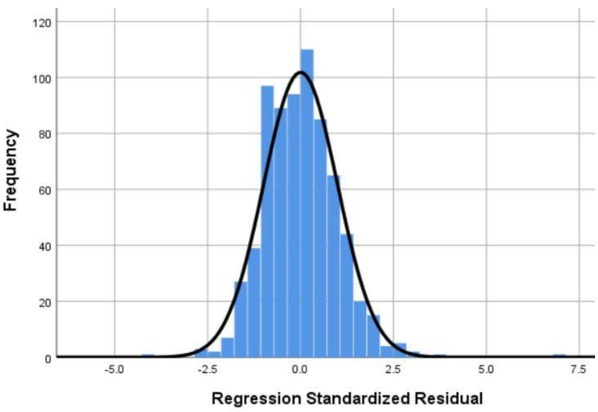


Figure 4. Histogram related to the normal distribution of the proposed model of linear regression method in Tabriz metro line 2 tunnel

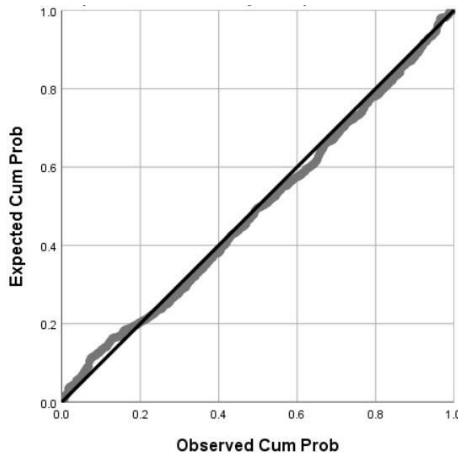


Figure 5. P-P diagram of the linear regression model

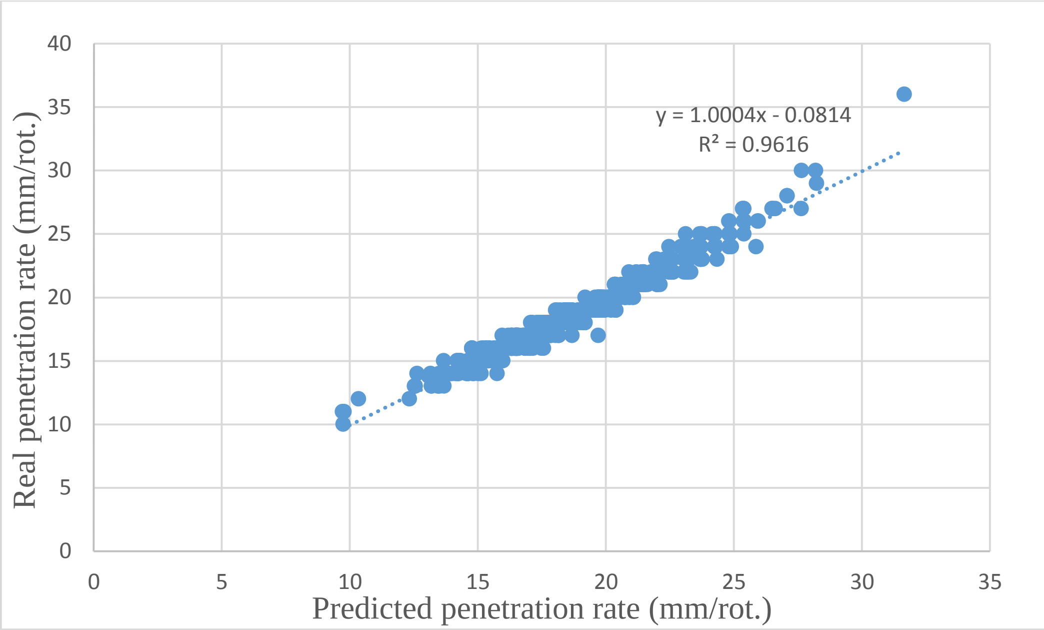


Figure 6. Correlation between the predicted values of the linear regression method and the actual penetration rate in the Tabriz metro line 2 tunnel.

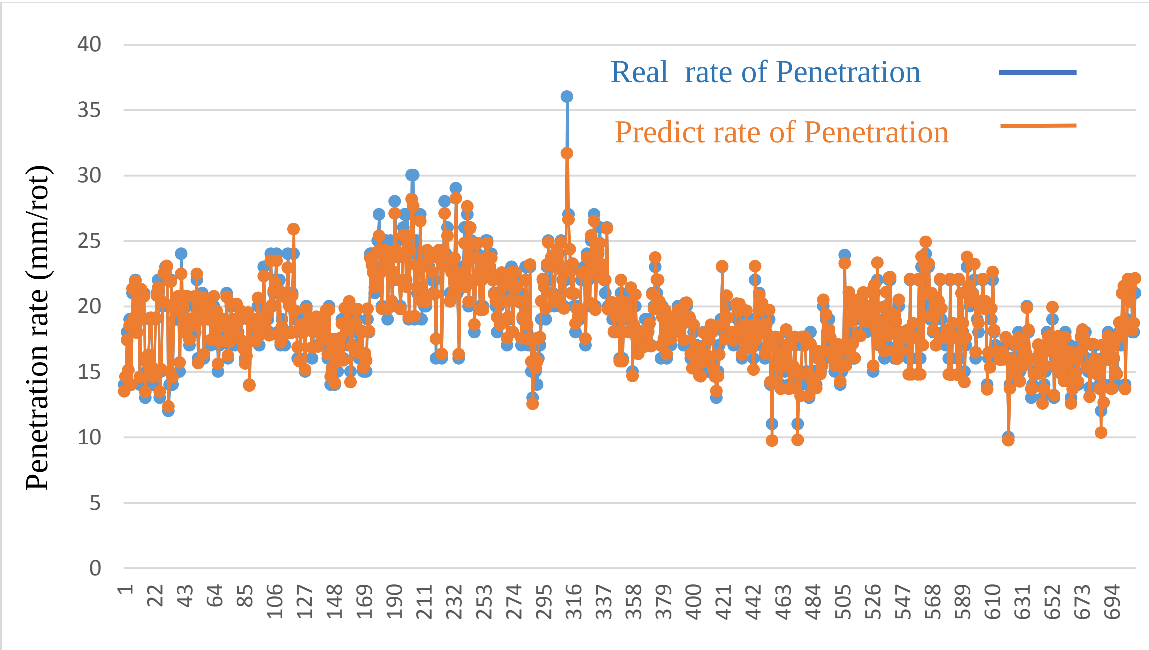


Figure 7. Comparison of predicted and actual values of the penetration rate of the linear regression method in Tabriz metro line 2 tunnel

5. PREDICTING THE PENETRATION RATE OF EPB MACHINE USING THE FUZZY METHOD

Mamdani and Sugeno algorithms were applied to predict the penetration rate of the EPB machine in line 2 of Tabriz metro, using the fuzzy method. Mamdani algorithm is one of the most common algorithms used in engineering and geology. The inputs along with the output were divided into 8 sections using a triangular function. The intensity of changes in these intervals is indicated by the letters (VVL, VL, L, ML, MH, H, VH, VVH). In the Mamdani algorithm, the range of transverse axis changes in the shape functions is between 0 and 1. The changes in the longitudinal axis also depend on the range of changes in the studied parameter. The shape functions are selected so that for each parameter, at least two functions overlap. This overlap can reach up to 50%. Figure 8 shows the input and output parameters in the Mamdani fuzzy logic model in the Tabriz metro line 2 tunnel. Also, in Figure 9, an example of the existing rules in the fuzzy logic method with the Mamdani algorithm in the Tabriz metro line 2 tunnel is shown. The statistical results obtained from the fuzzy logic method with the Mamdani algorithm are presented in Table 9. The correlation between the actual and predicted values of the Mamdani fuzzy logic model is shown in Figures 10 and 11.

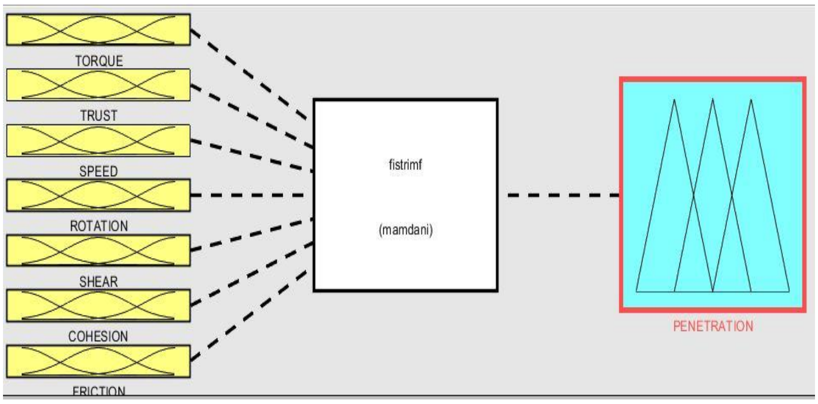


Figure 8. General shape of the inputs and outputs in the fuzzy logic method with Mamdani algorithm in Tabriz metro line 2 tunnel

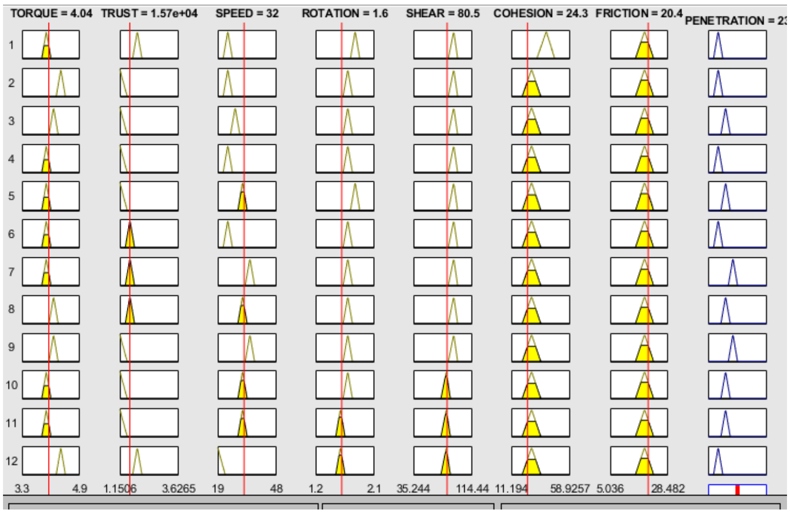


Figure 9. An example of the rules in the fuzzy logic method with Mamdani algorithm in the Tabriz metro line 2 tunnel

Table 9. Results of the fuzzy logic model with Mamdani algorithm in Tabriz metro line 2 tunnel

Model	Number of data	Number of rules	R^2	RMSE	VAF
Mamdani	711	561	0.9305	0.9497	89.22

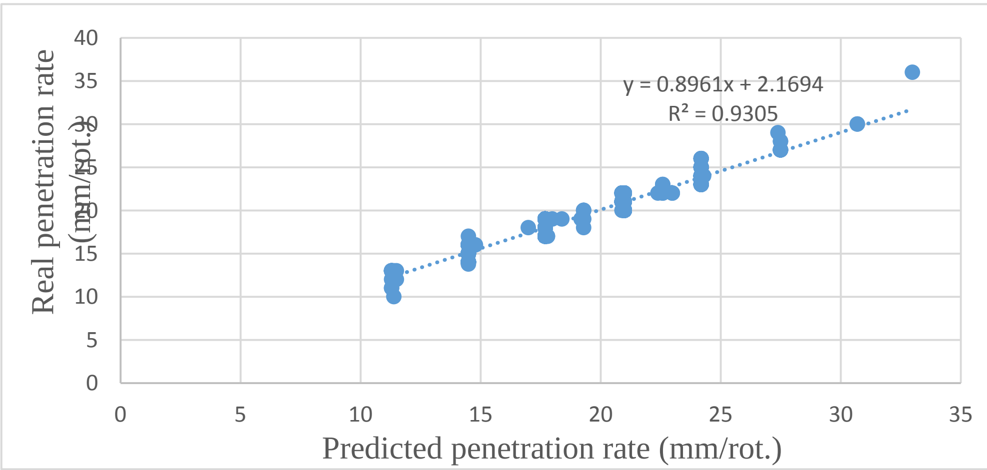


Figure 10. Correlation between the predicted values of Mamdani fuzzy logic model and the actual penetration rate in Tabriz metro line 2 tunnel

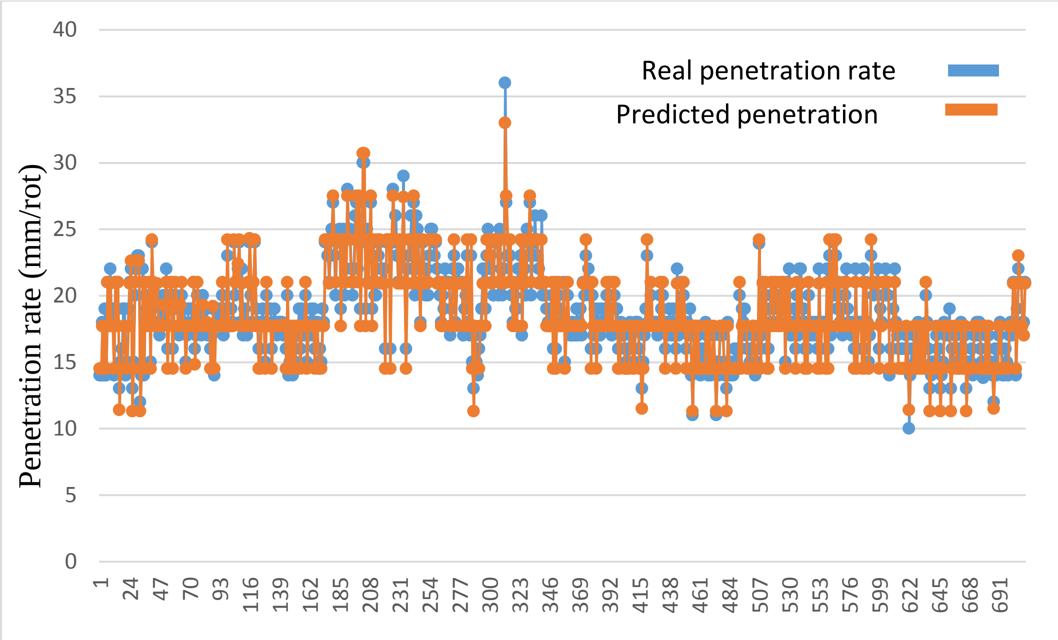


Figure 11. Comparison of the predicted and actual values of penetration rate with Mamdani fuzzy logic model in Tabriz metro line 2 tunnel

The schematic of the Sugeno algorithm is different from that of the Mamdani algorithm. In the Mamdani algorithm, the output type is expressed as a function, but in the Sugeno algorithm, this output includes fixed numbers and linear relations. Also, the method of averaging in the two algorithms is different. Sugeno fuzzy inference algorithm is mostly used in control systems, but in Mamdani fuzzy inference algorithm, logical results are expressed with a relatively simple structure that is mostly used in decision support systems. Figure 12 shows the schematic of the Sugeno algorithm used to predict the penetration rate of the EPB machine on line 2 of the Tabriz metro. Also, in Figure 13, an example of the existing rules in the fuzzy logic method with the Sugeno algorithm in the Tabriz metro line 2 tunnel is shown. The statistical results obtained from the fuzzy logic method with the Sugeno algorithm are presented in Table 10 as well. The correlation between the actual and predicted values of the Sugeno fuzzy logic model is shown in Figures 14 and 15. Comparison of Mamdani and Sugeno algorithms revealed that the values of the coefficient of determination (R^2), root mean square error (RMSE) and performance indicator (VAF) of the Sugeno algorithm was better than those of the Mamdani algorithm.

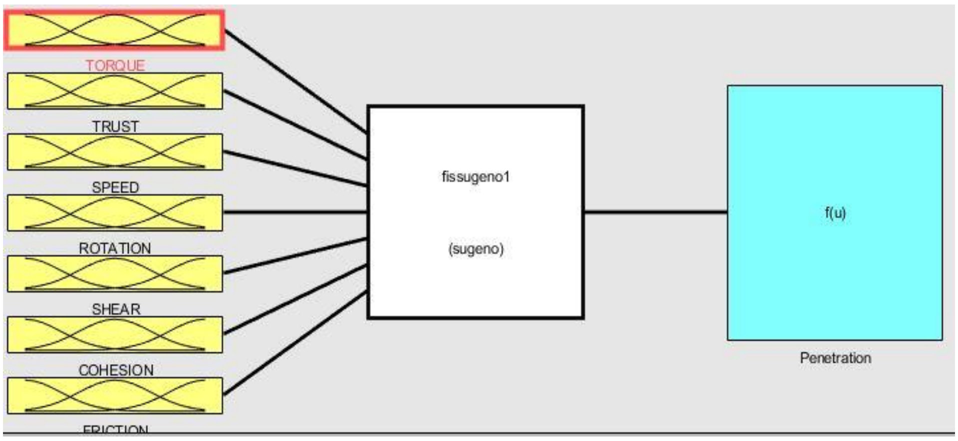


Figure 12. General shape of inputs and outputs in the fuzzy logic method with Sugeno algorithm in Tabriz metro line 2 tunnel

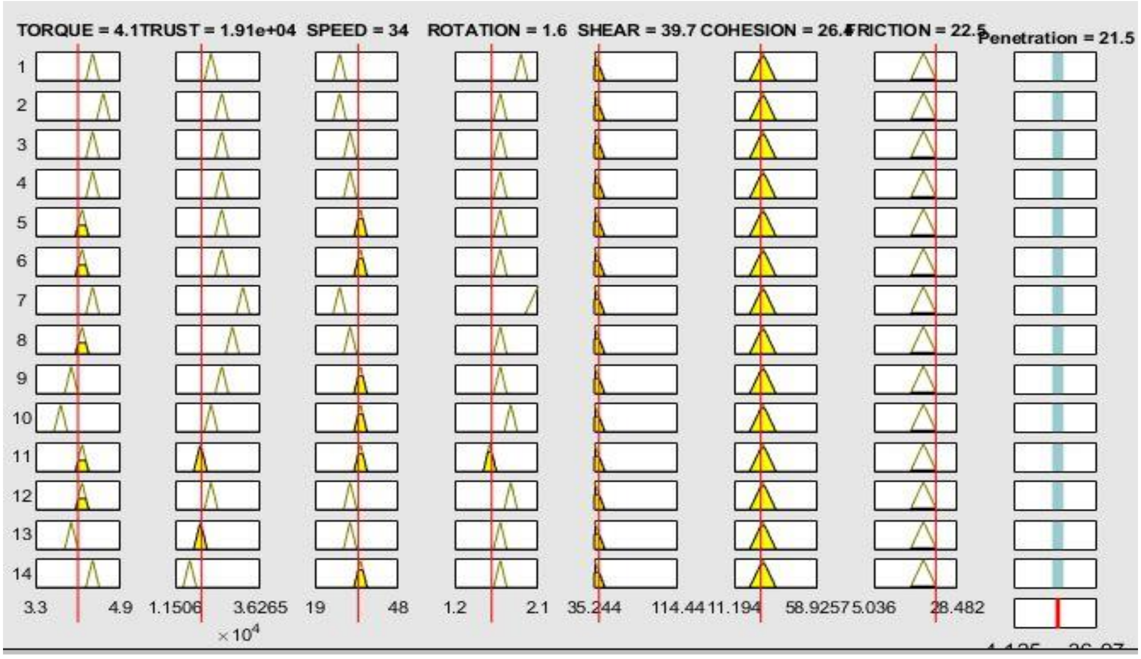


Figure 13. An example of the rules in the fuzzy logic method with Sugeno algorithm in Tabriz metro line 2 tunnel

Table 10. Results of the fuzzy logic model with Sugeno algorithm in Tabriz metro line 2 tunnel

Model	Number of data	Number of rules	R^2	RMSE	VAF
Sugeno	711	561	0.9493	0.7264	94.36

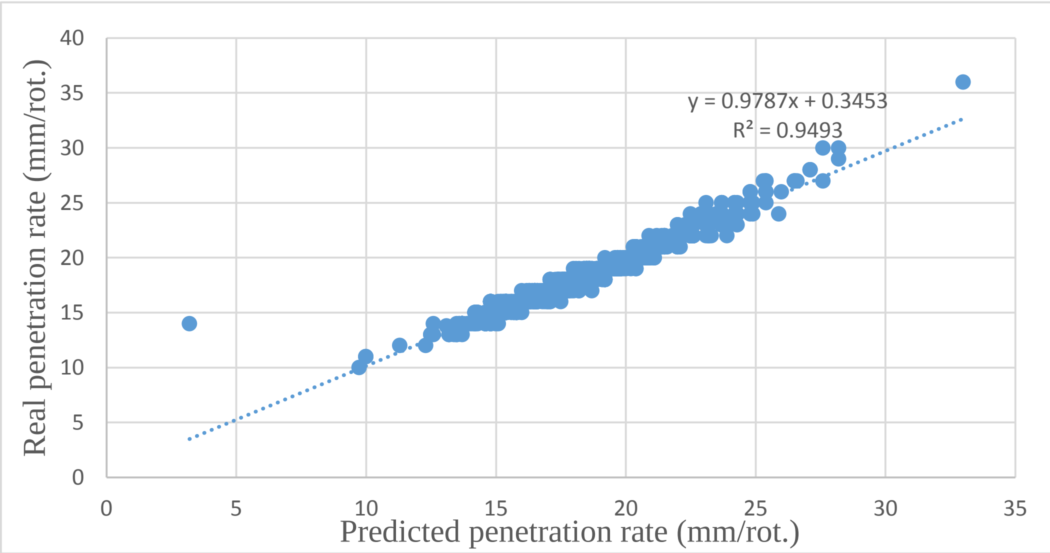


Figure 14. Correlation between the predicted values of the Sugeno fuzzy logic model and the actual penetration rate in Tabriz metro line 2 tunnel

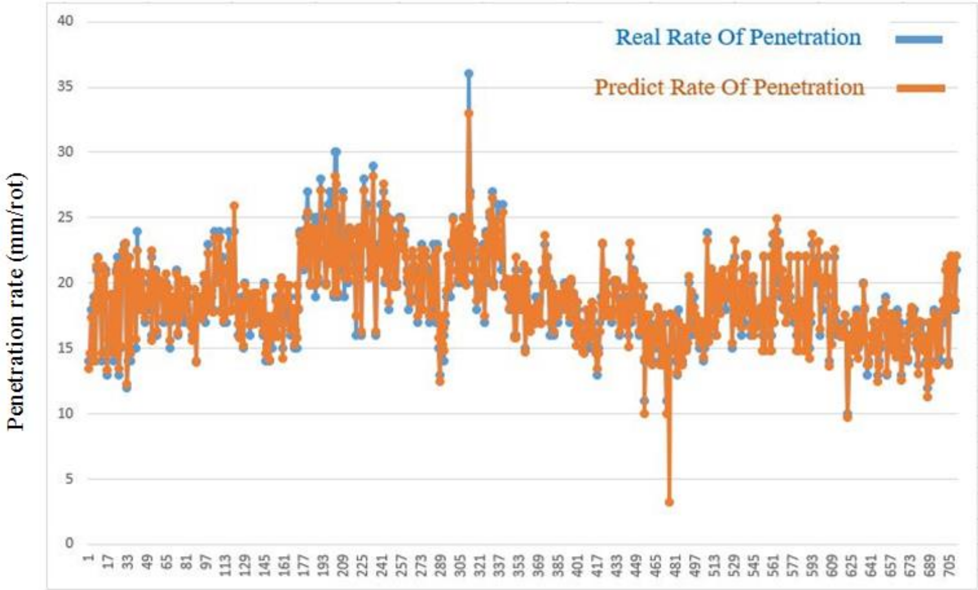


Figure 15. Comparison of the predicted and actual penetration rate with Sugeno fuzzy logic model in Tabriz metro line 2 tunnel

6. PREDICTION OF THE PENETRATION RATE OF EPB MACHINE USING ANFIS NEURO-FUZZY METHOD

The neuro-fuzzy method creates a fuzzy inference system using a set of input and output data. The parameters of the system membership functions are set by the after-diffusion algorithm or its combination with the least-squares method. A structure similar to that of neural networks can be used to change the mapping between input and output. Neural networks can be used to map inputs to membership functions and their parameters, and then to map the output membership functions to the outputs.

The modeling method used in the neuro-fuzzy method is similar to other system detection techniques. In the first step, a parametric system is assumed; then the input and output data are collected in the usable form of the neuro-fuzzy system. The neuro-fuzzy system can then be used to teach the fuzzy logic model. A schematic of the neuro-fuzzy system used in this study is shown in Figure 16. The neuro-fuzzy system also has seven input parameters, in accordance with other fuzzy logic methods of this study. The statistical results obtained from the neuro-fuzzy method are presented in Table 11. The correlation between the actual and predicted values of the Sugeno fuzzy logic model is shown in Figures 17 and 18.

The statistical results obtained from the fuzzy logic method with Mamdani and Sugeno algorithms, as well as the neuro-fuzzy method, are summarized in Table 12. This table shows that the values of the coefficient of determination (R2), root mean square error (RMSE) and performance indicator (VAF) of the neuro-fuzzy method is more appropriate than those of the Sugeno and Mamdani methods in fuzzy logic.

Table 11. The results of the neuro-fuzzy model in Tabriz metro line 2 tunnel

Model	number of data	Number of rules	R^2	RMSE	VAF
ANFIS	711	561	0.9615	0.6350	96.09

Table 12- Comparison of statistical results of Sugeno and Mamdani models with the neuro-fuzzy method in Tabriz metro line 2 tunnel

Model	Number of data	Number of rules	R^2	RMSE	VAF
Mamdani	711	561	0.9305	0.9497	89.22
Sugeno	711	561	0.9493	0.7264	94.36
ANFIS	711	561	0.9615	0.6350	96.09

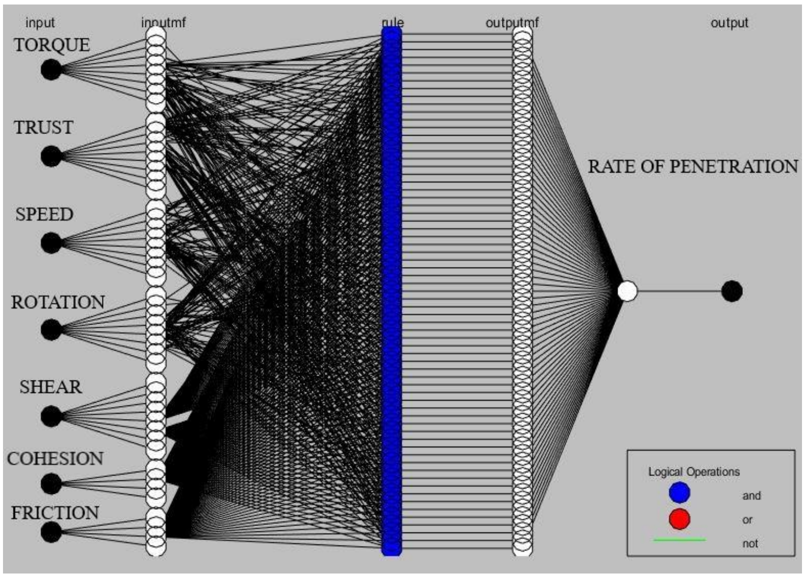


Figure 16. The schematic of the neuro-fuzzy system used in this study

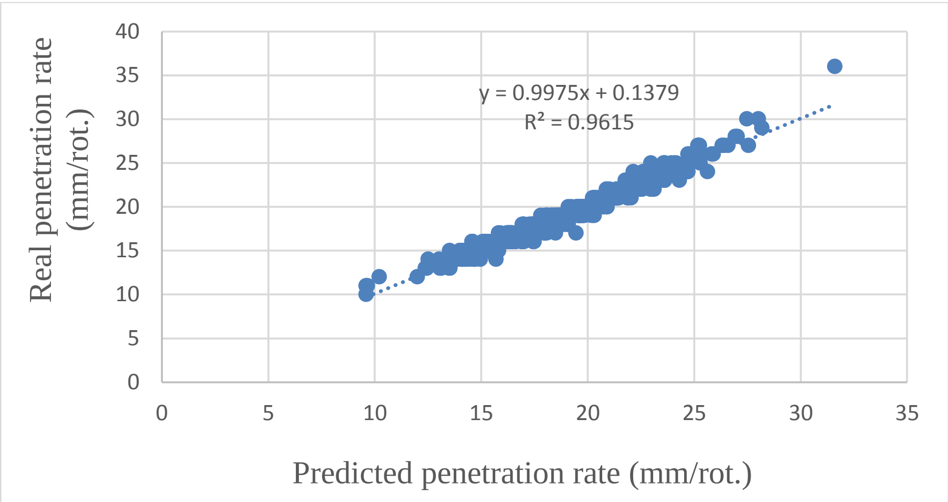


Figure 17. Correlation between the predicted values of the neuro-fuzzy model and the actual penetration rate in the Tabriz metro line 2 tunnel

7. PREDICTION OF THE PENETRATION RATE OF EPB MACHINE USING METAHEURISTIC ALGORITHMS

Meta-heuristic algorithms are one type of optimization algorithms that have solutions for exiting from local optimal points; so, they can be used in a wide range of problems. In this research, particle swarm optimization (PSO) algorithms, genetic algorithm (GA), whale optimization algorithm (WOA), and ant colony algorithm (ACO) were used to predict the penetration rate of earth pressure balance boring machine.

7.1. Prediction of EPB machine penetration rate using Particle Swarm Optimization (PSO) algorithm

A particle swarm optimization algorithm is a way to discover the problem's search space and to set the parameters needed to maximize a specific goal. This algorithm was introduced in 1995 by Kennedy and Eberhart [33]. This method has been adapted from the collective action of groups of animals such as birds and fish. In this algorithm, there are a number of creatures, called particles, that are scattered in the search space. Each particle calculates the value of the objective function in a position of the space in which it is located. It then selects a direction to move using a combination of current location information and the best location it has previously been in, as well as information from one or more of the best particles in the collection. After performing the collective move, one step of the algorithm is completed. These steps are repeated several times to finally get the answer [34]. Figure 19 shows the convergence graph of the PSO algorithm and Figure 20 represents the fitted diagram as well as the history of the error values of this algorithm in the Tabriz metro line 2 tunnel. The correlation between the actual and predicted values of the particle swarm algorithm is shown in Figure 21. The statistical results obtained from the particle swarm optimization algorithm in the Tabriz metro line 2 tunnel are summarized in Table 13.

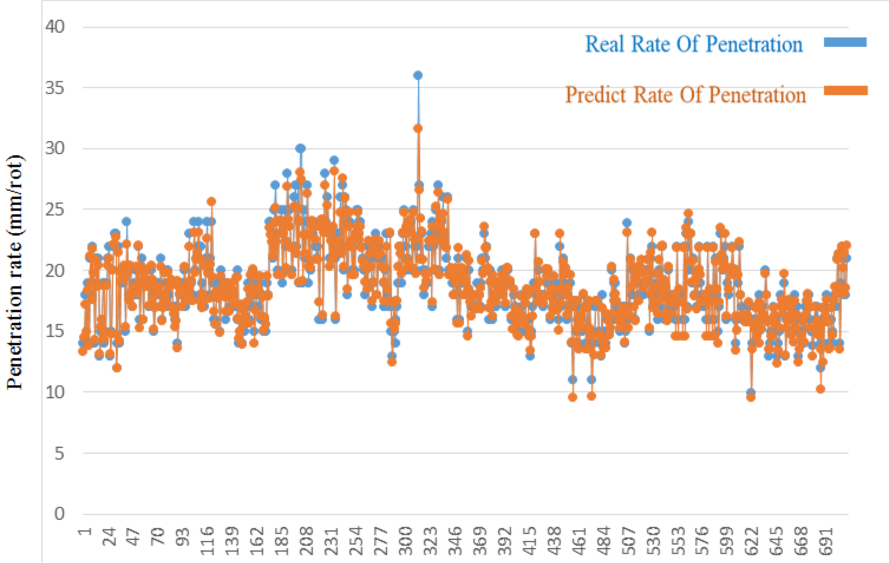


Figure 18. Comparison of the predicted and actual values of penetration rate with a neuro-fuzzy model in Tabriz metro line 2 tunnel

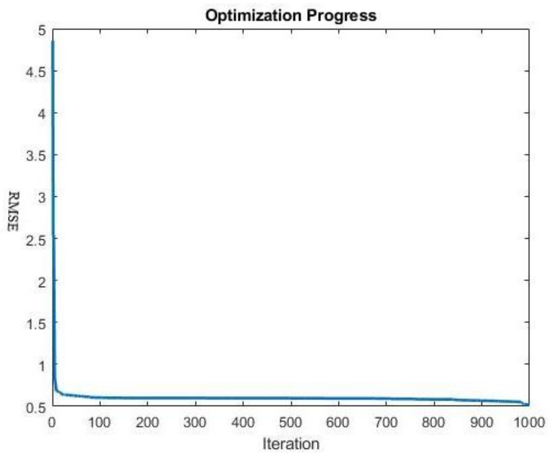


Figure 19. Convergence graph of the PSO algorithm

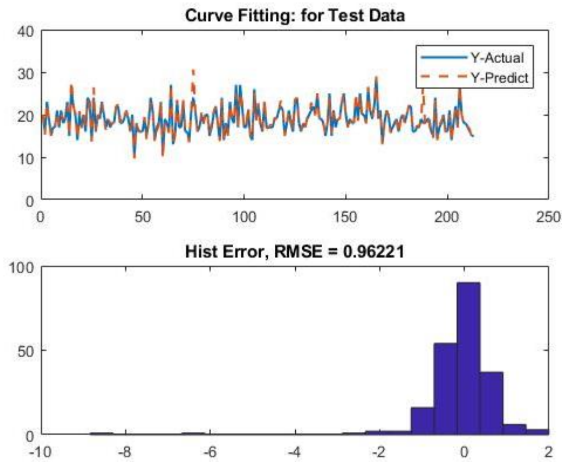


Figure 20. Top graph: The fitted curve of the PSO algorithm Bottom graph: History of the PSO model error values

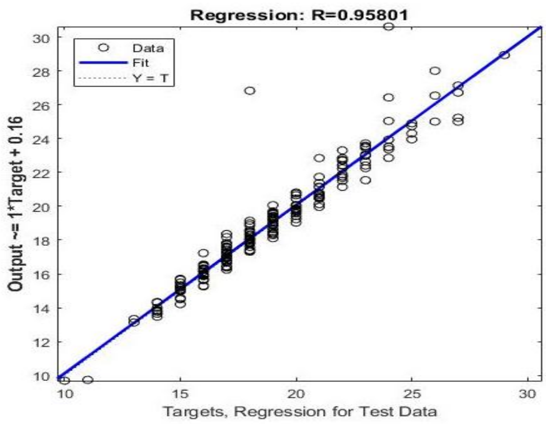


Figure 21. Comparison of the predicted and actual values of the penetration rate using PSO algorithm in Tabriz metro line 2 tunnel

Table 13. Results of the particle swarm optimization algorithm in Tabriz metro line 2 tunnel

Model	R^2	RMSE	VAF
PSO	0.9177	0.9622	87.69

7.2. Prediction of the EPB machine penetration rate using Ant Colony Algorithm (ACO)

The ant colony algorithm is a method inspired by the behavior of ants in finding the path between their nest and food, as proposed in 1992 by Dorigoa [35]. In this way, artificial ants move on the problem diagram and leave marks on it, like real ants, so that the next artificial ants can find better solutions to the problem. Figure 22 shows the convergence graph of the ACO algorithm and Figure 23 represents the fitted diagram as well as the history of the error values of this algorithm in the Tabriz metro line 2 tunnel. The correlation between the actual and predicted values of the ant colony algorithm is shown in Figure 24. The statistical results obtained from the various metaheuristic algorithms used in this paper are summarized in Table 14. This table shows that the coefficient of determination values in the ant colony algorithm is higher than those in other metaheuristic algorithms. Also, the mean error squares of this algorithm are less than those of other meta-heuristic algorithms and its performance index was higher in comparison to other meta-heuristic algorithms.

Table 14. Comparison of the statistical results of different meta-heuristic algorithms in Tabriz metro line 2 tunnel

Model	R^2	RMSE	VAF
PSO algorithm	0.9177	0.9622	87.69
Genetic algorithm (GA)	0.9543	0.6875	95.38
Whale optimization algorithm (WOA)	0.9581	0.6609	95.71
Ant colony algorithm (ACO)	0.9598	0.6468	95.90

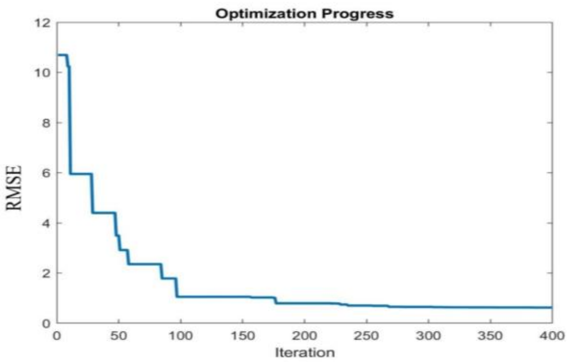


Figure 22. Convergence graph of the Ant Colony Algorithm (ACO)

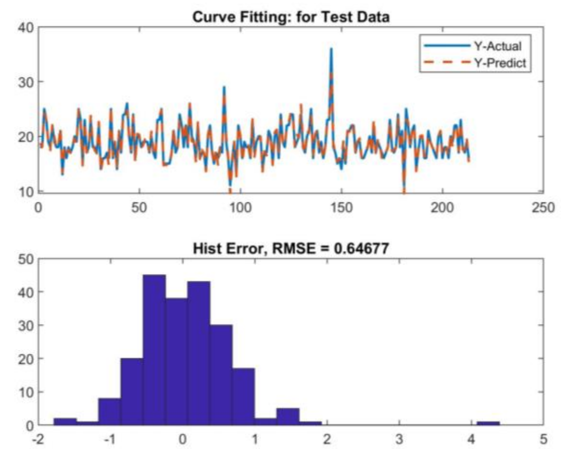


Figure 23. Top graph: The fitted curve of ant colony algorithm, bottom graph: Error history of ant colony algorithm

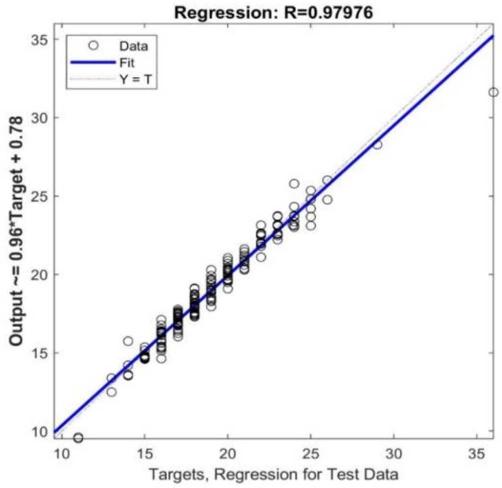


Figure 24. Comparison of the predicted and actual values of penetration rate using ACO algorithm in Tabriz metro line 2 tunnel

8. SENSITIVITY ANALYSIS

In this study, a sensitivity analysis was performed using the Cosine amplitude method, and the sensitivity of the modeled target (ROP) to the input parameters was determined. To use this method, all data pairs must be represented as an X-column array:

$$X = \{x_1, x_2, x_3, \dots, x_i, \dots, x_n\} \quad (8)$$

Each of the elements of X_i in the X is a vector with the length m:

$$x_i = \{x_{i1}, x_{i2} x_{i3}, \dots, x_{im}\} \quad (9)$$

The effect of each of the X input parameters on the objective function can be determined using Equation 10 [36]:

$$r_{ij} = \frac{\sum_{k=1}^{m} x_{ik} x_{jk}}{\sqrt{\sum_{k=1}^{m} x_{ik}^2 \sum_{k=1}^{m} x_{jk}^2}} \quad (10)$$

The results of the sensitivity analysis of the input parameters on the output of the model are shown in Figure 25. The results of the sensitivity analysis showed that all input parameters had a significant effect on the penetration rate of the EPB machine. The most and the least effect on the penetration rate of the EPB machine belonged to the cutter head torque and the friction angle of the soil, respectively.

9. CONCLUSIONS

One of the most widely used methods for the excavation of metro tunnels is mechanized drilling using a full-face boring machine. Tunnel drilling in cities has more complex and special conditions in comparison to other areas. In cities, due to the presence of surface structures, settlements, and urban facilities, tunnel excavation may face dangers such as subsidence of surface structures. Today, the use of earth pressure balance (EPB) boring machine is widespread, which reduces the risks of subsidence as much as possible. One of the most important parameters of the earth pressure balance machine is the penetration rate of the machine.

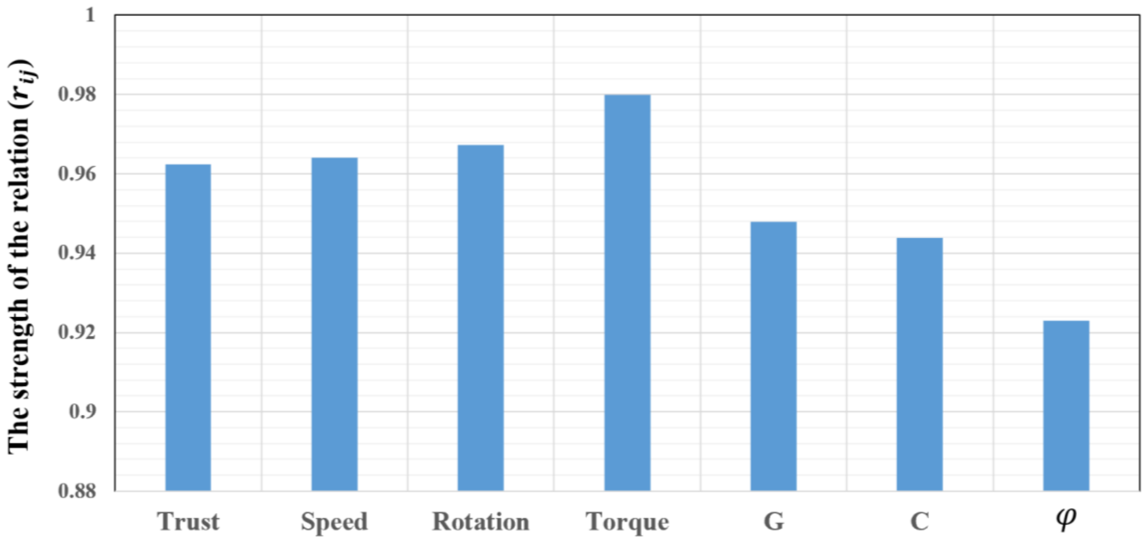


Figure 25. The results of the sensitivity analysis of the input parameters on the model output

Factors affecting the penetration rate of EPB machines are divided into three categories of geological and geotechnical factors, machine specifications, and operational parameters. Important geotechnical parameters include cohesion, friction angle, and soil shear modulus. Among the important parameters of the machine, we can name the thrust force of the jacks, torque, and rotation speed of the cutter head. Predicting the performance of these parameters in excavation projects is very important. Tabriz Metro Line 2 project, as one of the major projects in the northwest of the country, has complexities and risks such as liquefaction, soil cohesion, groundwater problem, and underground cavities such as aqueducts. Therefore, it is very important to predict the penetration rate of the EPB machine in Tabriz metro line 2 to reduce costs. Factors affecting the penetration rate, after principal component analysis, because they cover more than 95% of the changes, are torque, thrust force, velocity, rotation, shear modulus, cohesion, and friction angle. Box plots were used to show the outlier data. After deleting the outlier data, the number of data was reduced to 711. Then, the data were normalized between zero and one. To predict the penetration rate of the EPB machine in line 2 of Tabriz metro, linear regression methods, fuzzy logic using Mamdani and Sugeno algorithms, ANFIS neuro-fuzzy method, and meta-heuristic algorithms were used. The results of these studies can be summarized here:

1- Prediction of the machine penetration rate using linear regression method showed that the coefficient of determination of the obtained model was 0.92 and the P-P diagram of the linear regression model was close to the straight line and its distribution was normal.

2- The results of the fuzzy logic analysis using Mamdani and Sugeno algorithms showed that the coefficient of determination of Mamdani and Sugeno algorithms was higher than that of linear regression analysis. Also, the root mean square error in the Sugeno algorithm was 24% less than that of the Mamdani algorithm; further, its performance indicator was 6% higher than that of the Mamdani algorithm.

3- Prediction of the penetration rate in Tabriz metro line 2 tunnel using neuro-fuzzy analysis showed that the mean squares error in the neuro-fuzzy method was 55% and 23% less than that of fuzzy logic with Mamdani and Sugno algorithms, respectively.

4- The results of meta-heuristic algorithms for particle swarm optimization (PSO), genetic algorithm (GA), whale optimization algorithm (WOA), and ant colony algorithm (ACO) also showed that the ant colony algorithm was more accurate than other algorithms. Also, the mean squares error of this algorithm (RMSE) was less than those of other metaheuristic algorithms and its performance indicator (VAF) was higher in comparison to the rest of metaheuristic algorithms.

5- Examining the results of different methods used to predict the penetration rate of the earth pressure balance boring machine in the Tabriz metro line 2 tunnel showed that the neuro-fuzzy method had a more accurate prediction of the penetration rate of the EPB machine.

6- The results of the sensitivity analysis also showed that all input parameters had a significant effect on the penetration rate of the EPB machine. The most and the least effect on the penetration rate of the machine belonged to the cutter head torque and the friction angle of the soil, respectively.

REFERENCES

[1] Shi, H., Yang, H., Gong, G., & Wang, L. (2011). Determination of the cutter head torque for EPB shield tunneling machine. Automation in Construction, 20, 1087-1095.

[2] Bakhshandeh Amnieh, H., Zamzam, M. S., Moosavi, S. E., & Tarigh Azali, S. (2014). Selection of the most appropriate soil conditioning set in mechanized boring of Tehran metro line 7 tunnel. Tunneling & Underground Space Engineering (TUSE), 2(2), 145-154.

[3] Farmer, I. W., & Glossop, N. H. (1980). Mechanics of disc cutter penetration. Tunnels and Tunnelling International, 12(6), 622-625.

[4] Berke, L., & Hajela, P. (1991). Application of Neural Networks in Structural Optimization. NATO-DFG Advanced Study Institute on optimization of large structural systems, 2, 731-745.

[5] Barton, N. (2000). TBM Tunneling in Jointed and Faulted Rock, Balkema Publishers, Rotterdam.

[6] Sapigni, M., Berti, M., Bethaz, E., Busillo, A. & Cardone, G. (2002). TBM performance estimation using rock mass classifications. International Journal of Rock Mechanics and Mining Sciences, 39, 771-788.

[7] Jahed Armaghani, D., Koopialipoor, M., Marto, A., & Yagiz, S. (2019). Application of several optimization techniques for estimating TBM advance rate in granitic rocks. Journal of Rock Mechanics and Geotechnical Engineering, 11, 779-789.

[8] Faramarzi, L., Kheradmandian, A., & Azhari, A. (2020). Evaluation and optimization of the effective parameters on the shield tbm performance: torque and thrust-using discrete element method (DEM). Geotechnical and Geological Engineering, 38, 2745-2759.

[9] Zhao, J., Gong, Q.M., & Eisensten, Z. (2007). Tunnelling through a frequently changing and mixed ground: A case history in Singapore. Tunnelling and Underground Space Technology, 22, 388-400.

[10] Elbaz K, Shen, S. L., Zhou, A., Yuan, D. J., & Xu, Y. S. (2019). Optimization of EPB Shield Performance with Adaptive Neuro-Fuzzy Inference System and Genetic Algorithm. Applied Sciences, 9(4), 1-17.

[11] Chou, H. S., Yang, C. Y., Hsieha, B. J., & Chang, S. S. (2001). A study of liquefaction related damages on shield tunnels. Tunnelling and Underground Space Technology, 16,185-193.

[12] Ball, R. P. A, Young, D. Y., Isaacson, J., Champa, J., & Gause, C. (2009). Research in soil conditioning for EPB tunneling through difficult soils. In: Rapid excavation and tunneling conference, Las Vegas, USA, 320–333

[13] Zumsteg, R., Plotze, M., & Puzrin, A. M. (2013). Reduction of the clogging potential of clays: new chemical applications and novel quantification approaches. Geotechnique, 63(4), 276-286.

[14] Alavi Gharahbagh, E., Rostami, J., & Talebi, K. (2014). Experimental study of the effect of conditioning on abrasive wear and torque requirement of full face tunneling machines. Tunnelling and Underground Space Technology, 41, 127-136.

[15] Zhao, B., Liu, D., & Jiang, B. (2018). Soil conditioning of waterless sand–pebble stratum in EPB tunnel construction. Geotechnical and Geological Engineering, 36, 2495-2504.

[16] Mohammadi, S. D., Firuzi, M., & Asghari Kaljahi, E. (2016). Geological-geotechnical risk in the use of EPB-TBM, case study: Tabriz Metro, Iran. Bulletin of Engineering Geology and the Environment, 75, 1571-1583.

[17] Centis, S., & Giacomin, G. (2004). EPB tunnelling in highly variable ground–the experience of Oporto Light Metro. Tunnelling and Underground Space Technology, 19, 358.

[18] Carrieri, G., Fornari, E., Guglielmetti, V., & Crova, R. (2006). Torino metro line 1: use of three TBM-EPBs in very coarse grained soil. Tunnelling and Underground Space Technology, 21,274-275.

[19] Song, X., Liu, J., & Guo, W. (2010). A cutter head torque forecast model based on multivariate nonlinear regression for EPB shield tunneling. Proc. Int. Conf. Artif. Intell. Comput. Intell., 104-108.

[20] Toth, A., & Zhao, J. (2013). Evaluation of EPB TBM performance in mixed ground conditions. In: World Tunnel Congress, Switzerland-Geneva, 1149-1156.

[21] Barzegari, G., Uromeihy, A., & Zhao, J. (2014). EPB tunneling challenges in bouldery ground: a new experience on the Tabriz metro line 1, Iran.

Bulletin of Engineering Geology and the Environment, 73, 429-440.

[22] Namli, M., & Bilgin, N. (2017). A model to predict daily advance rates of EPB-TBMs in a complex geology in Istanbul. Tunnelling and Underground Space Technology, 62, 43-52.

[23] Avunduk, E., & Copur, H. (2018). Empirical modeling for predicting excavation performance of EPB TBM based on soil properties. Tunnelling and Underground Space Technology, 71, 340-353.

[24] Massinas, S., Prountzopoulos, G. K., Bhardwaj, V., Saxena, A., Clark, J., & Sakellariou, M. G. (2018). Design aspects of under-passing a city's heritage landmark with EPB machines under low overburden; The case of Chandpole Gate in Jaipur Metro, India. Geotechnical and Geological Engineering, 36, 3683-3705.

[25] Tzamos, S., & Sofianos, A. I., (2006). Extending the Q systems prediction of support in tunnels employing fuzzy logic and extra parameters. International Journal of Rock Mechanics & Mining Sciences, 43(6), 938-949.

[26] Zadeh, L. A. (1965). Fuzzy sets. Information and Control, 8, 338-353.

[27] Mamdani, E. H., & Assilian, S. (1975). An experiment in linguistic synthesis with a fuzzy logic controller. International Journal of Man-Machine Studies, 7(1), 1-13.

[28] Acaroglu, O., Ozdemir, L., & Asbury, B. (2008). A fuzzy logic model to predict specific energy requirement for TBM performance prediction. Tunnelling and Underground Space Technology, 23(5), 600-608.

[29] Wang, Y., & Chen, Y. (2014). A comparison of Mamdani and Sugeno fuzzy inference systems for traffic flow prediction. Journal of computers, 9(1), 12-21.

[30] Bezdek, J. C. (1981). Pattern Recognition with Fuzzy Objective Function Algoritms. Plenum Press, New York.

[31] Imensazen Consultant Engineers Institute (2009-2018). Tunnel Quality Control Reports and Route of Tabriz Metro line 2.

[32] Asgharzadeh Dizaj, M. (2019). Predicting Performance of Tunnel Boring Machine Using Fuzzy Logic Intelligent Method (Case Study: Tabriz Metro line 2), MSc Thesis, Sahand University of Technology.

[33] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. Proceedings of ICNN'95-International Conference on Neural Networks, Perth, Australia.

[34] Eberhart, R., & Kennedy, J. (1995). A new optimizer using particle swarm theory. Proceedings of the Sixth International Symposium on Micro Machine and Human Science, Nagoya, Japan.

[35] Dorigoa, M., & Blum, C. (2005). Ant colony optimization theory: A survey. Theoretical Computer Science, 344(2-3), 243-278.

[36] Darbor, M., Faramarzi, L., & Sharifzadeh, M. (2019). Performance assessment of rotary drilling using non-linear multiple regression analysis and multilayer perceptron neural network. Bulletin of Engineering Geology and the Environment, 78(3), 1501-1513.