RGNZ/MGPB

The prediction of EPB-TBM performance using firefly algorithms and particle swarm optimization

Rudarsko-geološko-naftni zbornik
(The Mining-Geology-Petroleum Engineering Bulletin)
UDC: 622.2
DOI: 10.17794/rgn.2023.5.7

Original scientific paper

Erfan Khoshzaher[1]; Hamid Chakeri[2]; Shahab Bazargan[3]; Hamid Mousapour[4]

[1] *Department of Mining Engineering, Sahand University of Technology, Tabriz, Iran, ORCID 0000-0001-8017-8498*
[2] *Department of Mining Engineering, Sahand University of Technology, Tabriz, Iran, ORCID 0000-0002-5734-5347*
[3] *Department of Mining Engineering, Sahand University of Technology, Tabriz, Iran, ORCID 0000-0002-5101-618x*
[4] *Department of Mining Engineering, Sahand University of Technology, Tabriz, Iran, ORCID 0000-0002-3999-8811*

Abstract
Penetration rate is one of the most important parameters in determining excavation time in tunnelling operations. Providing a prediction model or a mathematical relationship can give a better understanding of this issue. A mathematical equation between input and output parameters can be optimized by using algorithms such as Particle Swarm Optimization and Firefly. Since drilling operations interact between ground and machine, therefore, the effective parameters on the penetration rate are divided into two general categories such as machine and geological factors. Effective geological factors include internal friction angle, cohesion, specific gravity, shear modulus and groundwater level. In addition, the important parameters of TBM are torque, thrust jacks, and rotation speed. By defining an initial mathematical function, two optimization algorithms, which look for the most optimal mode, the goal here is the same as the mean square error (MSE). Finally, by examining and comparing the performance of two algorithms, using the coefficient of determination and the mean square error, it found that the Firefly algorithm has a better performance than the Particle Swarm Optimization algorithm.

Keywords:
EPB-TBM; penetration rate; regression; firefly algorithm; particle swarm optimization

1. Introduction

Tunnelling in urban areas due to the sensitivities in these areas has special problems. Nowadays, in urban areas, the use of earth pressure balance type TBM (EPB) has become much more widespread. One of the ways to predict the efficiency of these machines is to estimate their penetration rate. Penetration rate is the ratio of excavated distance to the time during continuous excavating. Penetration rate is usually expressed in mm per round of the excavator or metres per hour.

In general, with an increase in the speed of progress and the penetration rate, the duration of the project decreases. Checking and predicting the performance of the TBM and the parameters affecting it is done in order to increase the accuracy and speed of the work along with reducing the risks. For this purpose, in the first step, the parameters involved in the operation of the excavation machine, such as geological conditions and operational parameters of the excavation machine, are discussed. All the desired effective factors are collected using the previous data available from the excavations and geological studies and finally, using the available data, an accurate model for the penetration rate of the machine can be provided.

In general, with an increase in the speed of progress and the penetration rate, the duration of the project decreases. Considering the importance of predicting the penetration rate in tunnelling operations, researchers have always sought to find a method to predict penetration rate value at the same time as TBM construction and so far, many theoretical and experimental methods have been presented. **Yagiz and Karahan (2011)** presented a nonlinear relationship with the independent variables of uniaxial compressive strength, brittleness index, distance between weak plates and the angle between these plates and the tunnel axis, by using the particle swarm optimization algorithm by optimizing the coefficients of a nonlinear equation.

Torabi et al. (2013) investigated two parameters of efficiency and penetration rate of the Tehran-North highway service tunnel using neural networks and statistical methods. The input parameters of the models that are used in this research are: uniaxial compressive strength, internal friction angle, Poisson's ratio and cohesion, and it was found that geotechnical parameters have the greatest effect on the penetration rate of the device. **Salimi and Esmaili (2013)** predicted the penetration rate by us-

Corresponding author: Hamid Chakeri
e-mail address: h.chakeri@gmail.com

ing variables of uniaxial compressive strength, Brazilian tensile strength, distance of weak plates, slope index and angle between these plates and tunnel axis and using multivariable linear regression methods, multivariable nonlinear methods and neural networks.

Salimi et al. (2016) predicted the performance of TBMs in hard rock by using non-linear regression analysis and artificial intelligence with different predictive parameters such as UCS, RQD, BTS. **Gao and Li (2015)** predicted the penetration rate of TBM using Support Vector Machine (SVM). **Gholamnejad and Tayarani (2010)** used artificial neural network to predict the penetration rate. **Jamshidi (2018)** used multiple regression analysis to predict the penetration rate of TBM using the brittleness index. **Fatemi et al. (2018)** performed a sensitivity analysis on the input parameters with different models for predicting the performance of different TBMs. **Arbabsiar et al. (2020)** provided a new model, to predict the advance rate of the TBM, in hard rock conditions. The obtained results showed that the newly proposed linear model has better performance than the other models. Machine learning and deep learning methods excel in solving complex mapping problems and have increasingly found successful applications in the engineering field **(Yu et al., 2021; Yu et al., 2023). Mousapour et al. (2023)** studied functional parameters of TBM, including penetration rate, on TBM performance, using laboratory simulated machine.

Figure 1: EPB machine used in the Tabriz metro line 2

In this study, an attempt has been made for accurate calculations and predictions of the behavior and penetration rate of EPB TBM by using two well-known and widely used swarm intelligence algorithms, PSO and FFA. Among the parameters involved in this relationship, we can mention the main parameters of the device as torque, force of thrust jacks, and cutter head rotation speed, and the geological parameters include internal friction angle, cohesion, specific weight, shear modulus, and water level.

2. The study area

Tabriz metro line 2 is one of the urban train routes of the Tabriz metro system. This route is about 22.4 kilometres long and includes 22 stations. It starts from the area of Qaramelk Lands, after passing Vahdat St. and Qaramelk Square (the first station), Akhoni St., Qods St., Meydane Kohan, Daneshsara Square, it enters Abbasi St. and it extends to Shahid Fahmideh Square and ends at Tabriz International Exhibition after passing Bagh Misheh and Marzdaran. The outer diameter of the tunnel of the Tabriz metro line 2 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 studied area, the depth of the tunnel varies from 15 to 28 meters. Excavation is done using an EPB machine. **Figure 1** shows the EPB machine used in the excavation of Tabriz metro line 2.

In this section, based on observations from boreholes and by examining the results of field and laboratory tests, considering the results of geotechnical studies of projects close to the scope of the project and based on engineering judgment, the geotechnical parameters for the design of different layers of soil and rock for the length of the tunnel are presented.

Table 1: Statistical values related to the investigated variables

Parameter		Min	Max	Average		Standard deviation	Variance
		Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
Machine parameters	Torque (MN.m)	1.1	5.3	4.1347	0.0137	0.3474	0.121
	Thrust (KN)	7195	36265	22371	186.86	4734.7981	22418.313
	Speed (mm/min)	5	55	33.3	0.188	4.7746	22.797
	Penetration rate (mm/rot)	4	36	19.09	0.144	3.6576	13.378
Geological parameters	Internal friction angle (°)	5.04	28.48	15.58	0.229	5.8062	33.712
	Cohesion (KPa)	11.19	58.93	41.35	0.449	11.3885	129.699
	specific weight ()	1.82	1.97	1.89	0.0017	0.045	0.002
	Shear modulus ()	28.52	155.2	71.42	1.088	27.5891	761.159
	Water table (m)	11	17.8	14.66	0.077	1.9554	3.824

 pp. 79-86, DOI: 10.17794/rgn.2023.5.7

By examining the results of field and laboratory tests, according to the results of geotechnical studies of projects close to the study area and based on engineering judgment, geotechnical parameters have been proposed.

The data set for machine parameters is obtained from excavation data from stations 1 to 3. Geotechnical data are also obtained from the results of field and laboratory tests. For both Gaussian regression and SVM used in this study, eight input variables including machine parameters such as torque (MN.m), thrust jack force (KN), speed (mm/min) and penetration rate (mm/rot) and geological parameters such as internal friction angle (°), cohesion (KPa), specific weight () and water table (m) were used. The only output in this study is the penetration rate (mm/rot). **Table 1** shows the maximum, minimum, average, standard deviation and variance values of each parameter.

3. Firefly algorithm

The firefly algorithm (FA) is one of the newest optimization algorithms based on swarm intelligence, which was first introduced by Yang (**Yang, 2009; Yang 2010; Yang 2010**). This algorithm works similar to the PSO and BFO algorithms and even by choosing appropriate values for the parameters used in the FA algorithm, its performance can be standardized to a large extent similar to the PSO algorithm. FA algorithm has been mainly used to solve continuous optimization problems in unconstrained mode. Also, recently efforts have been made to solve the combined optimization problems using the FA algorithm (**Sayadi et al., 2010**).

Solving unconstrained continuous optimization problems using the firefly algorithm:

1. Initializing the parameters. Appropriate values are attributed to the parameters in which:
   γ: Attenuation coefficient, Max generation (Algorithm termination condition), : The maximum attraction factor between two fireflies, α: Coefficient of random displacement vector and m: The number of fireflies (The variable t is the counter of the number of repetitions performed).
2. Initialization of fireflies. An initial population of fireflies (a set of vectors) randomly generated in the problem domain.
3. The light intensity of the ith firefly. is determined by using the value obtained for the objective function at the point .
4. If t < Max Generation then go to step 5, otherwise go to step 11.
5. For m: i = 1 do steps 6 and 7.
6. Perform step 7 for m: j=1.
7. If then move the ith firefly to the jth firefly. For this purpose, update the position of the ith firefly using the following **Equation 1**:

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

Where:

β – attractiveness coefficient,

r_{ij} – means the distance between ith and jth firefly.

8. Randomly change the position of the best firefly.
9. Sort the fireflies based on the values obtained for the cost function and determine the best answer obtained.
10. Go to step 4.
11. Introduce the best solution obtained during all iterations as the solution to the optimization problem.

In the seventh step, the algorithm of **Equation 1** is used in order to move the less bright firefly towards the brighter firefly. Generally, this equation can be written as **Equation 2**:

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

Where:

β – attractiveness coefficient.

r_{ij} is defined as **Equation 3**:

$$r_{ij} = \left\| x_i - x_j \right\| = \sqrt{\sum_{k=1}^{n}\left(x_{i,k} - x_{j,k}\right)^2} \quad (3)$$

In the above equation, means the kth component of the position vector of the ith firefly (x_i). It is obvious that in **Equation 1**, due to the presence of term $\beta_0 e^{-\gamma r_{ij}^2}$, the intensity of light received from the jth firefly by the ith firefly decreases with an increase of the distance between these two fireflies, and as a result, the degree of tendency of the ith firefly, also decreases towards the jth firefly (which is in a more optimal position). It should be noted that if the environment is isolated, the coefficient of the second term on the right side in **Equation 1**, instead of $\beta_0 e^{-\gamma r_{ij}^2}$, should be considered for example in the form of **Equation 4**:

$$\beta = \frac{\beta_\circ}{r_{ij}^2} \quad (4)$$

On the other hand, in an environment with a constant attenuation coefficient (γ), the received light intensity at a point at a distance r from the light source, is determined by equation $I(r) = I_0 e^{-\gamma r}$, where is the light intensity of the source. Therefore, in **Equation 1**, the combination of the above two properties (i.e. the law of the inverse of the square of the distance and the law of light attenuation with a constant coefficient by the environment) has been used to determine the amount of attenuation of a firefly towards a brighter firefly. Obviously, theoretically, instead of using coefficient $\beta_0 e^{-\gamma r_{ij}^2}$ in **Equation 1**, any other descending function can be used to define "attractiveness". For example, in reference (**Lukasik and Zak, 2009**), the second term on the right side of **Equation 1**, is considered as **Equation 5**:

$$\beta = \beta_\circ e^{-\gamma r_{ij}^2} \quad (5)$$

Also, in reference (**Yang, 2009**), it is suggested to use a lower attractiveness coefficient like **Equation 6**:

$$x_i \leftarrow x_i + \beta_\circ e^{-\gamma r_{ij}^2} + \alpha\left(rand - \frac{1}{2}\right) \quad (6)$$

Since in **Equations 1**, **5** and **6** for $r_{ij} = 0$, β becomes β_0, so we call β_0 as maximum attractiveness.

It should be noted that, due to the presence of two nested loops in the FA algorithm, the complexity of this algorithm is of order O(m^2). Therefore, the increase in the number of fireflies may increase the computational load of the algorithm and as a result, its inefficiency. However, this increase, leads to an increase in the global optimal solution.

3.1. Choosing the right values of the parameters in the FA algorithm

In the FA algorithm, the effect of fireflies on each other is determined using the attractiveness coefficient (β). The attractiveness coefficient is also affected by two other parameters: the maximum attractiveness coefficient β_0 and the attenuation coefficient γ. The parameter β_0 represents the attractiveness between two fireflies when both of them are in the same place (maximum possible attractiveness). Generally, β_0 should be a number between zero and one. In the limiting case, by choosing $\beta_0 = 0$, actually a memoryless random search is performed in each firefly which searches for the answer alone without cooperating with other fireflies. In the limiting case $\beta_0 = 1$, the brightest firefly attracts light with all the power of other fireflies (especially those in its neighborhood). In most of the simulations, using $\beta_0 = 1$ leads to relatively satisfactory results.

On the other hand, the γ parameter determines how to reduce the attenuation of fireflies towards each other by increasing the distance between them. For γ=0, the attenuation of fireflies to each other, independent of the distance between them, will be equal to a constant number, which is contrary to the way fireflies work in nature. For γ→∞, the attractiveness of fireflies decreases to zero, which leads to a random search (without collective cooperation) in the problem space. **Yang (2010)** suggested the using of γϵ[0,10]. In addition, **Lukasik and Zak (2009)** also recommended to use the values of **Equations 7** and **8** for this purpose, where γ_0 ϵ[0,10] and r_{ij} according to **Equation 9**.

$$\gamma = \frac{\gamma_0}{r_{\max}} \quad (7)$$

$$\gamma = \frac{\gamma_0}{r_{\max}^2} \quad (8)$$

$$r_{ij} = \left\| x_i - x_j \right\|, \forall x_i, x_j \in S \quad (9)$$

S is the set of all points in the domain of the optimization problem.

The last parameter used in **Equation 1**, is α, a coefficient. In most applications, α can be chosen as a number between zero and one. Note that if α=1 is selected, all the variables of the optimization problem will be randomly shifted by ±0.5 to their nominal values.

4. Particle swarm optimization algorithm

Particle swarm optimization (PSO) is another optimization method inspired by nature, which was invented to solve numerical optimization problems with a very large search space without the need to know the gradient of the objective function. This method was invented and published for the first time in 1995 by **Kennedy and Eberhart (1995)**. This algorithm is inspired by the group life of animals, including insects (such as ants, termites, bees, etc.), birds and fish.

So far, the PSO algorithm has been successfully used to solve many applied optimization problems, including neural network training, power distribution network optimization, process identification, etc. Although efforts are being made to solve combined optimization problems using the PSO algorithm, its application has been mainly limited to solving continuous optimization problems.

4.1. Laws governing animal densities of particles

The mass movement of any animal density of particles can be modelled, using the following three simple laws:

1. Separation (Not too close to each other);
2. Alignment (Moving towards the average of other group members);
3. Cohesion (staying together).

4.2. Solving unconstrained continuous optimization problems using PSO algorithm

1. Initialization: giving an initial value to a population of particles with random positions and velocities in D dimensions in the search space;
2. Estimation: making an estimate for the fitness of each particle in this population;
3. Update: The speed of each particle is calculated with **Equation 10**, movement to the next position is done based on **Equation 11** and θ of each particle is calculated with **Equation 12** (**Shi and Eberhart, 1998a; Shi and Eberhart, 1998b**):

$$V_j(i) = \theta(i)V_j(i-1) + c_1 r_1\left[P_{best,j} - X_j(i-1)\right] + \\ + c_2 r_2[G_{best} - X_j(i-1)] \quad (10)$$

$$X_j(i) = X_j(i-1) + V_j(i); j = 1,2,\ldots,N \quad (11)$$

$$\theta(i) = \theta_{\max} - \left(\frac{\theta_{\max} - \theta_{\min}}{i_{\max}}\right) i \quad (12)$$

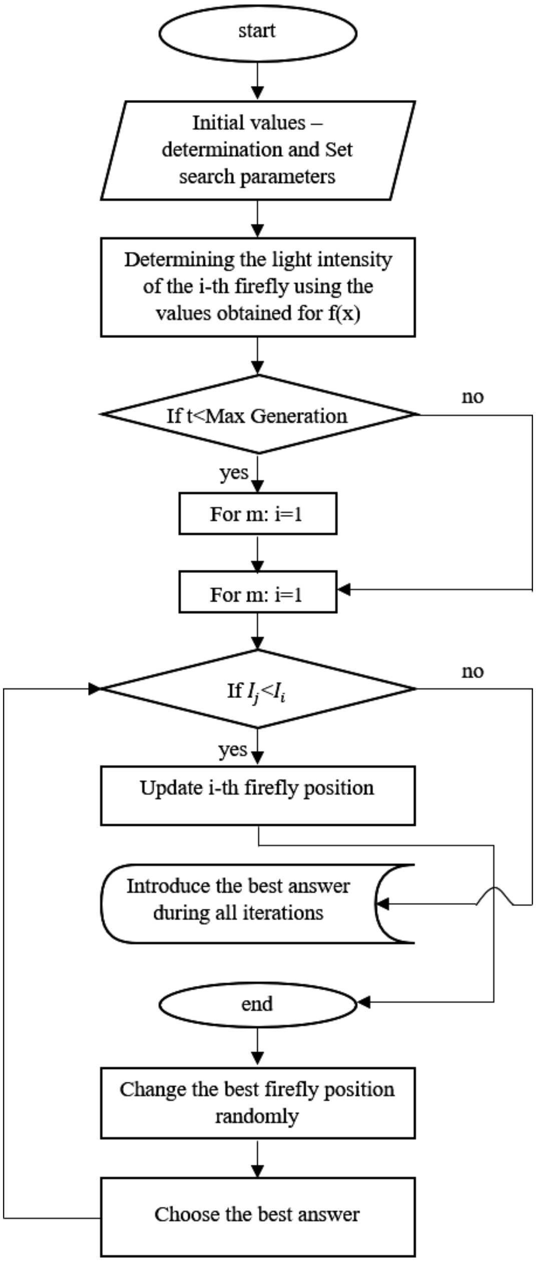

Figure 2: Firefly optimization algorithm

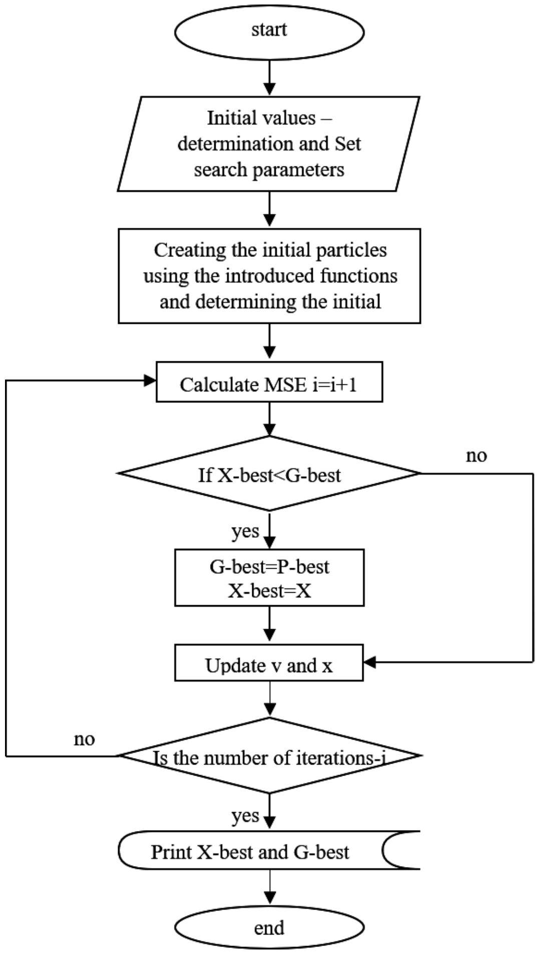

Figure 3: Particle swarm optimization algorithm

Where:

θ_{max} – initial value of the inertia weight,

θ_{min} – final value of the inertia weight,

i_{max} – maximum number of repetitions in the PSO algorithm (in order to terminate its execution).

As mentioned before, in most cases, values of $\theta_{max} = 0.9$ and $\theta_{min} = 0.4$ are used for this purpose. These values, which were obtained experimentally and by performing many and varied simulations, lead to satisfactory results in most problems (**Xinchao, 2010; Du et al., 2016**). The firefly optimization algorithm and the particle swarm optimization algorithm are given in **Figures 2** and **3**.

5. Fitness function and error values

The mean square error (MSE) is a very common measure to obtain the best estimate, which is particularly desirable among statisticians. Using this criterion, the estimate with the lowest mean square error is selected. In statistics, the mean square error of an estimate expresses the mean squared difference between the actual value and what was predicted. The fact is that the error of the mean square is always positive (and not zero) either because it is random or because the estimator does not account for information that could produce a more accurate estimate. **Equation 13** is used to calculate the mean squared error:

$$\mathrm{MSE} = \frac{1}{n}\sum\nolimits_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{13}$$

R-squared correlation is displayed almost everywhere with the symbol R^2, is the most popular measure of the goodness of fit of the model and consists of the square of the correlation coefficient between y and $\hat{y}$ (i.e. the second power of the correlation coefficient between the actual values of the dependent variable and the estimated values obtained from the model). The correlation coefficient should be between -1 and 1. As a result, R^2 which is its second power, will be between zero and one. If this correlation is high, the model fits the data well (**Steel and Torrie, 1960; Glantz et al. 1990; Draper and Smith, 1998**). The R-squared correlation is shown in **Equation 14**:

$$\left(R^2\right) = 1 - \frac{\sum(\mathrm{y_i} - \hat{y}_\mathrm{i})^2}{\sum(\mathrm{y_i} - \overline{y}_\mathrm{i})^2} \tag{14}$$

6. Objective function

Here, the most important issue is calculating the penetration rate as a parameter that collects the effect of all important parameters on the boring machine, which is known as the objective function. The results of **Equation 15** which is optimized by two algorithms and its optimal coefficients are used in calculating the mean square error MSE (error values) and calculating the R-squared correlation (Fitness function). There are 9 unknown coefficients (from w to w_8) in this equation

$$xROP = w + w_1 \times Torque + \frac{w_2}{Trust} + w_3 \times Speed + w_4 \times Friction +$$

$$+ w_5 \times \ln\left(Cohension\right) + \frac{w_6}{Density} + w_7 \times Shear + w_8 \times WT \tag{15}$$

where torque is in mega-newton metres , thrust force is in kilonewtons , speed is in millimetres per minute , penetration rate is in millimetres per rotation (mm/rot), friction angle in degrees, cohesion in kilopascals , soil specific gravity in gr/m^3, shear modulus in (kg/cm^2) and the height of the water table in metres .

7. Analysis of results and comparison

In the discussed algorithms, the objective function is evaluated, which shows the value of each parameter or design. In this way, the selection of the objective function in the algorithm is very important. The function that has optimized coefficients, is in the form of a nonlinear equation. In **Table 2**, the most optimal coefficients obtained from the implementation of two algorithms are given.

Table 2: The most optimal coefficients obtained from the implementation of two algorithms

w	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
-0.6014	-1.4167	2.1367	0.6081	-0.1331	-0.7976	0.1751	-0.0096	0.7296

Table 3: The results obtained from the optimization models

Model properties	PSO	FA
Number of data	642	642
Repetition times	1000000	40
MSE	4.310	3.341
R	0.870	0.890
R^2	0.756	0.792
CPU-time (s)	70.500	50.070

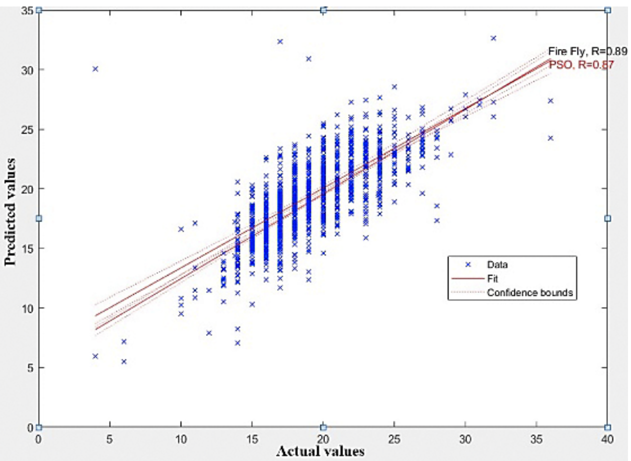

Figure 4: Correlation diagram of two PSO and FA algorithms

In the mentioned optimization problems, the objective function is the mean square error function and this function is one of the most important compared between the three mentioned methods. As seen in **Table 3**, the firefly algorithm (FA) with an error value of 4.541 and a correlation coefficient of 0.792 has one of the best performances among the two compared methods.

The correlation chart between the actual and predicted values can be seen in **Figure 4** that obtained determination coefficient by the FA optimization algorithm is better than the PSO algorithm.

In innovative methods, getting a more accurate answer at any cost is not acceptable. Time as the only cost factor can be an important factor in choosing the most optimal method in such problems. In general, the firefly

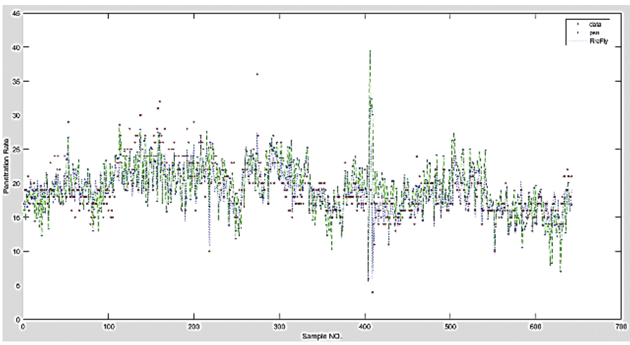

Figure 5: Predicted values by two PSO and FA algorithms and real values

Copyright held(s) by author(s), publishing rights belongs to publisher, pp. 79-86, DOI: 10.17794/rgn.2023.5.7

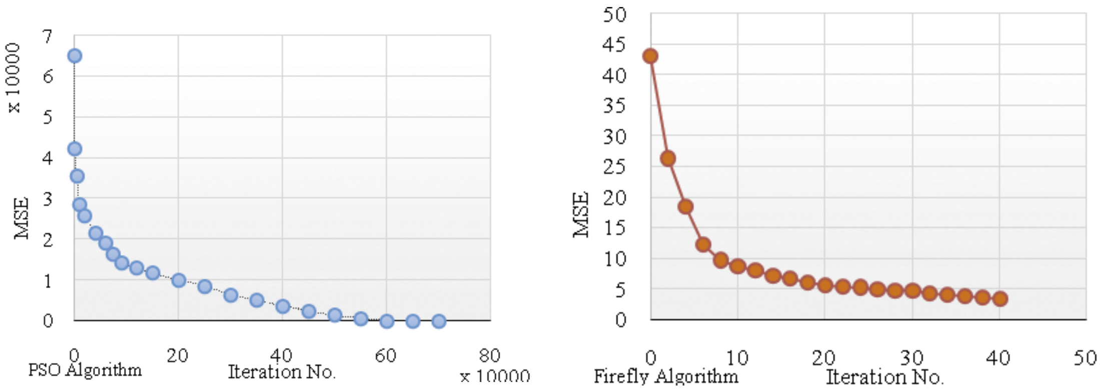

Figure 6: Convergence of PSO and Firefly algorithm during iteration steps

algorithm has been selected as the best method among the optimization methods. The graph of **Figure 5** is a comparison between the convergence of the predicted and actual solutions, the FA algorithm has better accuracy by a small distance.

By repeating the steps and increasing the number of steps, the coefficients of the equation gradually converge to a specific number. In this case, the values of the fitness function gradually take a downward trend and decrease. In the diagram of **Figure 6**, the convergence of the error values resulting from the implementation of the PSO algorithm in different stages can be seen.

8. Conclusion

Penetration rate is the most important factor in checking the efficiency of the full-section excavation machine. In order to get the most accurate estimate of the penetration rate in this study, the most up-to-date and smart computing methods have been used. From the calculation methods, the types of linear, non-linear, Gaussian regressions and regression by support vector machine can be mentioned. The investigated parameters separated as machine and geological variables. The variables of the machine are torque, thrust force and rotation speed of the cutterhead. The variables of the geological parameters are the angle of internal friction, cohesion, wet specific gravity, shear modulus and water table.

Two optimizer algorithms were used and compared in the study (PSO and firefly algorithms). Among the two optimizer algorithms, the firefly algorithm has better accuracy. The error caused by the firefly algorithm (MSE=3.341) has a lower rate than the particle swarm algorithm (MSE=4.310). The minimum error value for the firefly algorithm was obtained in a minimum number of iterations compared to the particle swarm algorithm. Also, its computing time is less. The error obtained from both algorithms is at a level less than unity, which is acceptable for the proposed problem and indicates sufficient accuracy of the presented models.

The models reviewed in this study are user-friendly in terms of application, due to executing a specific code, compared to methods such as prediction with ANN (artificial neural networks) and fuzzy systems. Artificial neural networks and fuzzy methods include hidden layers and equations, which are unfamiliar to users, so particle swarm and firefly models are superior in this respect. These two algorithms can be used more in tunnel-related topics in the future due to having the necessary accuracy.

9. References

Arbabsiar, M. H., Farsangi, M. A. E., and Mansouri, H. (2020): A new model for predicting the advance rate of a Tunnel Boring Machine (TBM) in hard rock conditions. Rudarsko-geološko-naftni zbornik, 35(2). https://doi.org/10.17794/rgn.2020.2.6

Draper, N., and Smith, H. (1998): Applied regression analysis. Wiley interscience, New York, USA, 716p.

Du, K. L., Swamy, M. N. S., Du, K. L., and Swamy, M. N. S. (2016): Particle swarm optimization. Search and Optimization by Metaheuristics: Techniques and Algorithms Inspired by Nature, 153-173.

Fatemi, S.A., Ahmadi, M., and Rostami, J. (2018): Evaluation of TBM performance prediction models and sensitivity analysis of input parameters. Bulletin of Engineering Geology and the Environment, 77, 501-13.

Gao, L., and Li, X-b. (2015): Utilizing partial least square and support vector machine for TBM penetration rate prediction in hard rock conditions. Journal of Central South University, 22, 290-5.

Gholamnejad, J., and Tayarani, N. (2010): Application of artificial neural networks to the prediction of tunnel boring machine penetration rate. Mining Science and Technology (China), 20, 727-33.

Glantz, S.A., Slinker, B.K., and Neilands, T.B. (1990): Primer of applied regression and analysis of variance. NewYork. McGraw-Hill.

Jamshidi, A. (2018): Prediction of TBM penetration rate from brittleness indexes using multiple regression analysis. Modeling Earth Systems and Environment, 4, 383-94.

Kennedy, J., and Eberhart, R. (1995): Particle swarm optimization. In Proceedings of ICNN'95-international conference on neural networks, 4, 1942-1948.

Łukasik, S., and Żak, S. (2009): Firefly algorithm for continuous constrained optimization tasks. In Computational Collective Intelligence, 97-106.

Mousapour, H., Chakeri, H., Darbor, M., and Hekmatnejad, A. (2023): Evaluating the wear of cutting tools using a tunnel boring machine laboratory simulator. Mining of Mineral Deposits, 17(2). https://doi.org/10.33271/mining17.02.028

Salimi, A., and Esmaeili, M. (2013): Utilising of linear and non-linear prediction tools for evaluation of penetration rate of tunnel boring machine in hard rock condition. International Journal of Mining and Mineral Engineering, 4(3), 249-264.

Salimi, A., Rostami, J., Moormann, C., and Delisio, A. (2016): Application of non-linear regression analysis and artificial intelligence algorithms for performance prediction of hard rock TBMs. Tunnelling and Underground Space Technology, 58, 236-46.

Sayadi, M., Ramezanian, R., and Ghaffari-Nasab, N. (2010): A discrete firefly meta-heuristic with local search for makespan minimization in permutation flow shop scheduling problems. International Journal of Industrial Engineering Computations, 1, 1-10.

Shi, Y., and Eberhart, R. (1998a): A modified particle swarm optimizer. International conference on evolutionary computation proceedings, 69-73. http://dx.doi.org/10.1109/icec.1998.699146

Shi, Y., and Eberhart, R. C. (1998b): Parameter selection in particle swarm optimization. In Evolutionary Programming VII: 7th International Conference, 591-600. https://doi.org/10.1007/BFb0040810

Steel, R. G. D., and Torrie, J. H. (1960): Principles and procedures of statistics. with special reference to the biological sciences.

Torabi, S. R., Shirazi, H., Hajali, H., and Monjezi, M. (2013): Study of the influence of geotechnical parameters on the TBM performance in Tehran–Shomal highway project using ANN and SPSS. Arabian Journal of Geosciences, 6, 1215-1227.

Xinchao, Z. (2010): A perturbed particle swarm algorithm for numerical optimization. Applied Soft Computing, 10(1), 119-124.

Yagiz, S., and Karahan, H. (2011): Prediction of hard rock TBM penetration rate using particle swarm optimization. International Journal of Rock Mechanics and Mining Sciences, 48(3), 427-433.

Yang, X. S. (2009): Firefly Algorithms for Multimodal Optimization. Berlin, Heidelberg, Springer Berlin Heidelberg.

Yang, X. S. (2010): Firefly algorithm, stochastic test functions and design optimisation. International journal of bio-inspired computation, 2(2), 78-84.

Yang, X. S. (2010): Nature-inspired metaheuristic algorithms. Luniver press, 148p.

Yu, H., Qin, C., Tao, J., Liu, C. and Liu, Q. (2023): A multichannel decoupled deep neural network for tunnel boring machine torque and thrust prediction. Tunnelling and Underground Space Technology. 133, 104949.

Yu, H., Tao, J., Huang, S., Qin, C., Xiao, D. and Liu, C. (2021): A field parameters-based method for real-time wear estimation of disc cutter on TBM cutterhead. Automation in Construction. 124, 103603.

SAŽETAK

Predviđanje strojnoga EPB-TBM bušenja algoritmima krijesnice i optimizacije rojem čestica

Brzina bušenja jedan je od najvažnijih parametara u određivanju vremena strojnoga iskopavanja tunela. Izrada modela procjene ili matematičke međuovisnosti može pomoći boljem razumijevanju toga izazova. Matematička jednadžba međuovisnosti između ulaznih i izlaznih parametara može se optimizirati korištenjem algoritma optimizacije rojem čestica i algoritma krijesnice. Budući da je bušenje u interakciji između tla i stroja, efektivni parametri brzine bušenja podijeljeni su u dvije opće kategorije, a to su strojni i geološki čimbenici. Učinkoviti geološki čimbenici jesu: kut unutarnjega trenja, kohezija, specifična težina, modul smicanja i razina podzemne vode, a važni parametri TBM stroja jesu okretni moment, potisak cilindra i brzina vrtnje. Dva navedena optimizacijska algoritma traže najbolji način rada za postizanje vrijednosti srednje kvadratne pogreške definiranjem početne matematičke funkcije. Ispitivanjem i usporedbom procjene dvaju algoritama, prema koeficijentu determinacije i srednje kvadratne pogreške, utvrđeno je kako algoritam krijesnice ima bolje procjene od algoritma optimizacije rojem čestica.

Ključne riječi:
EPB-TBM, brzina bušenja, regresija, algoritam krijesnice, optimizacija roja čestica

Author’s contribution

Erfan Khoshzaher (1) (PhD candidate of Mining Engineering) wrote the paper and the presentation of the results. **Hamid Chakeri (2)** (PhD, Associate Professor) proposed the idea and guided the research. **Shahab Bazargan (3)** (MSc graduated of Mining Engineering) provided the firefly algorithms and particle swarm optimization data. **Hamid Mousapour (4)** (PhD candidate of Mining Engineering) wrote the paper.