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Analysis of the Performance of Cutting Tools of Tunnel Boring Machine (TBM) in Silty-Sand Soils Using Artificial Neural Network (ANN) – Case Study: Tabriz Metro Line 2 Project

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Abstract: The choice of cutting tools for soil excavation has a significant impact on the performance of tunnel boring machines. In this study, the data of two excavated sections of the Tabriz metro line 2 project have been used, and the crossed soils were sandy silts. Two sections have investigated the performance of two kinds of cutting tools (disk cutters and rippers). The cutting tools used in the first section of the drilling route are disc cutters, while in the second section, rippers have been used. To predict and evaluate the performance of the two types of cutting tools in silty-clay soils, artificial neuron networks were used, and the Levenberg-Marquardt algorithm was chosen for training the ANNs. Three important TBM parameters (torque, thrust force, and speed) were considered as input parameters, and the TBM penetration rate is chosen as the output variable in the developed artificial neuron network models. The obtained results showed that the best-predicted value obtained from the ANN was obtained with one hidden layer that contains four neurons. Finally, considering the performance parameter observed in silty soils, the ripper's performance is better compared to the disc cutter one.

Key words: Tunneling, cutting tools, disc cutter, ripper, artificial neural network.

Introduction

Nowadays, due to traffic and limited space in urban areas, tunneling and underground excavations are necessary to develop cities. One of the common methods is the use of tunnel boring machines (TBM). Nowadays, TBMs are widely used in projects to excavate subways and service tunnels (water and power transmission, etc.). Over the excavation time of these underground projects, maintenance costs for this machine are high. One of the main challenges that engineers have to face is the efficiency increase of the mechanized drilling machines and their cost decrease.

One of the most commonly used types of TBM is the earth pressure balance (EPB). With the development of tunneling, settlement control is one of the major challenges of geotechnical engineers. The EPB-TBM uses self-priming pressurised earth and some additives (such as greases, bentonite, etc.) to support the tunnel face. Controlling the EPB's parameters has a significant importance when excavating soft soils. For this reason, engineers should try to determine the performance of the machine parameters in different conditions.

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The most important factors, which affect the drilling performance, are the cutting tools and their layout. Different cutting tools have different functions depending on the geological conditions. Cutters, rippers, and scrappers are three types of cutting tools, which can be used. The cutters used for cutting and digging rocks harder than 100 MPa, the TBM cutting heads are endowed with cutters that put the surface of the rock under shear stress caused by the penetration of the cutter's rings. Scrapers and rippers are the most common cutting tools for removing sedimentary and metamorphic rocks, with compression resistance not exceeding 80 MPa, moderate hardness, and good penetrability—though often not without a high abrasion—are one of our specialties.

Recently, researchers have had to perform laboratory tests and finite element numerical modeling to obtain information on how they can operate the excavation depending on the geological conditions. Most studies have been carried out on cutting tools in rock environments, and soil environments were rarely studied. Abu Bakar et al. (2015) investigated the moisture content impact on the rock behaviour and rock excavation by disc cutters. Wang et al. (2015) identified the process of hard rock disc cutter wear and analysed it by quantifying the energy change. Qi et al. (2013) presented a cutter layout optimisation method for full-face rock tunnels boring machines. Their method is based on the Grey Relational Analysis, which is used to adjust the position angle and radius of each cutter.

Sun et al. (2018), based on the bearing stress on disc cutters, have assembled radii of the cutters to create a comprehensive evaluation model. It has permitted us to estimate the optimal values for the design layout of disc cutters. Cheng et al. (2017) investigated rock fragmentation under different installation polar angles based on a particle flow code. Studies on the prediction of the EPB-TBM performance, especially in soil, are very limited. Avunduk and Copur (2018) investigated soil components and related them to TBM base parameters (torque, thrust force, etc.) and gave an excavation performance prediction of an EPB-TBM by empirical relationships. Bilgin and Algan (2012) investigated the drilling machine performance using bentonite injection around the shield into fractured rocks and observed a decrease in the shield blockage and the TBM performance parameters such as the torque, thrust force, and advance rate.

Kasper and Meschke (2004) used finite element simulation with all relevant components to better predict the TBM performance and the ground reaction in soft soils. Maynar and Rodriguez (2005), using discrete elements numerical (DEM) modeling, investigated torque, thrust jacks forces, and earth pressures depending on the soil and stability. Wu and Qu (2009) proposed DEM simulations to investigate the chamber pressure system of an EPB-TBM in conditioned sands. Lambrughi et al. (2012) used the 3D finite element numerical method to simulate the EPB-TBM excavation process in different soil conditions.

An inverse method with in-situ data was used by Zhang et al. (2013) to predict drilling machine performance. Ates et al. (2014), based on a database from different TBM projects, suggested empirical models for determining the specifications of different hard and soft ground TBM types. Copur et al. (2014) used a stochastic model integrated into a deterministic model to estimate the EPB-TBM performance for a rock media excavation. Zhang et al. (2016) used thrust forces as the only component to predict the cutter head-ground interaction considering a mechanical decoupling analysis. Gao and Li (2015) predicted the penetration rate of a TBM by presenting the support vector machine (SVM) and the partial least squares regression (PLSR) models. Afradi et al. (2019) proposed SVM and artificial neural network (ANN) models to predict the TBM penetration rate in a rock media and the machine parameters.

One of the essential parameters for checking the performance of a TBM is its penetration rate. Using an appropriate cutting tool in TBMs, drilling speed is increased, and thus time and cost of the drilling operation are reduced. This paper studied the efficiency of two types of cutting tools (disk cutter and ripper) in silty-clay soils. The penetration rate is taken as the output parameter for comparison. The artificial neural network is used to predict the penetration rate for the two sections. The input parameters of the ANN are the thrust force, torque, and speed of the TBM machine. The penetration rate's predictive values permitted the selection of the appropriate cutting tools for excavation in silty-clay soils.

Tabriz Metro Line 2

The second line of Tabriz urban railway, approximately 22 km, includes 20 stations. Its specific goal is to transport people from the Qaramalek town in the west to the Basij square in the east of Tabriz.

An earth pressure balance tunnel boring machine (EPB-TBM) has been used to excavate the tunnel for a length of 1969 m, with an excavation diameter of 9.49 m. Until station 1, a disc cutter was used and after that changed to rippers and disc cutters. The soil conditioning was performed with a very low foam concentration ratio of approximately 0.5%. The foam expansion and foam injection ratios were equal to 8 and 100 % throughout the studied tunnel sections.

Soil Profile

The soil profile is similar in both sections (see Figure 1). The excavated soil was mainly silty clay on the entire tunnel route. Soil geomechanical parameters are given in Table 1. The parameters variation is very low.

Cutting Tools

The quality and lifetime of the excavation tools have a noticeable effect on the tunneling performance. The cutting tools are the most important part of the machine by the fact that they are in contact with the soil or rock mass at the tunnel face. The cutters, rippers, and scrappers are three types of cutting tools commonly used in TBM. The pattern of cutting tools can vary, but in general, the cutting tools are divided into three central, intermediate, and peripheral groups after installation.

- Central cutting tools: This group excavates the tunnel face as a pilot tunnel, and roller cutters are generally used in this section. The task of the central cutting tool is to start drilling and prepare the tunnel face for the other cutting tools.
- Intermediate cutting tools: These tools are selected as disks or rollers and used in the soft ground depending on nature and soil rigidity. They are installed perpendicular to the digger plate. This group of cutting tools is located in the middle of it, and they do a major part of the excavation.
- Peripheral cutting tools: In the peripheral part of the drilling plate, cutting tools are used to cut the tunnel face and maintain the tunnel shape. Disks or rollers can be used here. These tools allow a necessary gap to be created between the outer edge of this tool and the tunnel face.

Table 1: Soil geomechanical parameters

	Density (kg/m^3)	*Cohesion (kPa)*	*Internal Friction Angle (°)*	*Modulus of Elasticity (kPa)*
Section 1	1670-1700	5-10	28-30	30-32
Section 2	1650-1750	5-10	31-33	33-35

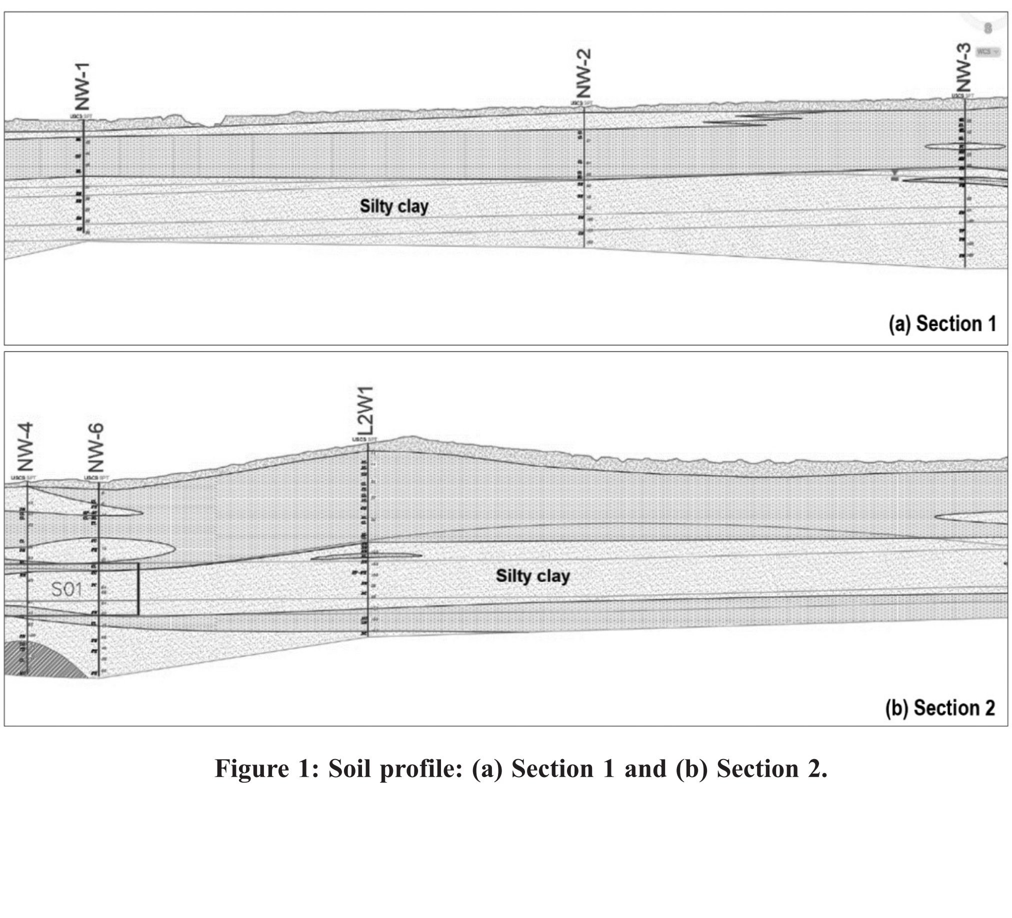

Figure 1: Soil profile: (a) Section 1 and (b) Section 2.

In each of the two studied sections, the cutting tools are of cut-to-disk type. The center and middle cutters in the first section are disc cutters, and in the second section, rippers.

Artificial Neural Networks (ANN)

The pattern of a biological structure and functioning model of the brain can be expressed using mathematical models. An ANN consists of neurons and connecting layers between these neurons. A simple ANN consists of an input layer, a hidden layer, and an output layer. More complex neural networks can have several hidden layers. In this study, the greatest number of hidden layers used in the adopted neural network structure is two. Given the proposed values in Table 2. In these neural networks, a range of 1 to 7 neurons was used to the hidden layer.

Table 2: Existing relationships for determining the hidden layer neurons

Hecht-Nielse (1989)	$\leq 2 \times N_i + 1$
Ripley (1993)	$(N_i + N_o)/2$
Paola (1994)	$\dfrac{2 + N_o \times N_i + 0.5 N_o \times (N_0^2 + N_i) - 3}{N_i + N_o}$
Wang (1994)	$2N_i /3$
Masters (1993)	$\sqrt{N_i \times N_o}$
Kaastra and Boyd (1996), Kanellopoulos and Wilkinson (1997)	$2N_i$

Input Parameters

It is difficult to determine all the relevant parameters that can influence the penetration rate. Furthermore, not all the parameters are independent, and some of them are strongly correlated. Hence, it is not essential to use all the variables as input parameters. The selected parameters affecting the rate of penetration (ROP) used in this study are the machine torque, thrust jacks force, and speed of TBM.

This study was conducted to determine the efficiency of the cutting tools for one soil type, and soil parameters were not included in this study. Data was obtained from Tabriz urban railway line 2 project:

- Section 1 (S1) (600 m – 400 rings) was excavated by disc cutters.
- Section 2 (S2) (600 m – 400 rings) was excavated by rippers and disc cutters.
- 386 data set was used from Section 1.
- 267 data set was used from Section 2.

The data obtained from these two sections are statistically presented in Table 3.

Input Data Set

The first stage in the ANN technique is data collection. Before training and implementation, the data set was divided randomly into training, validation, and test subsets. In the present study, 594 data sets were collected from Section 1 and 411 related to Section 2. About 65% of the data were chosen for training, 15% for validation, and 15% for the final test. These data are presented in Table 1. The training sets were used to generate the model, and the validation set was used to check the model's generalisation capability.

ANN Topology

An appropriate architecture was obtained from feed-forward backpropagation. A three-layer network with logarithmic sigmoid transfer function neurons in the hidden layer, and a purely linear transfer function neuron corresponding to the ROP in the output layer, was chosen. A trial and error procedure was used to identify the best network for this particular problem. Several network topologies were then examined.

Table 3: Statistics of the available input parameters

	Torque (MN.m)		*Thrust Force (MN)*		*Speed (mm/min)*		*Penetration rate (mm/rot)*	
	S1	*S2*	*S1*	*S2*	*S1*	*S2*	*S1*	*S2*
Max.	6.10	4.90	42.5	35	39	46	22	39
Min.	2.90	3.30	20.1	12	12	19	6	12
Std. Deviation	0.56	0.27	4.7	5.3	4.36	4.63	2.51	5.59
Var.	0.31	0.077	22357	28020	19.03	21.43	6.3	31.31

The Levenberg-Marquardt algorithm was chosen for training the ANNs because it is known to be the faster method for training moderate-sized feed-forward neural networks. The resulting target network should produce a minimum error for the training pattern and give a generalised solution that performs well with the testing pattern. Nonlinear (logarithmic sigmoid, tangent sigmoid) and linear (positive linear, pure linear) functions can be used as transfer functions. The most familiar and effective function in our case was the tangent sigmoid function (TANSIG), defined as Eq. (1):

$$f = \frac{2}{1+e^{-2n}} - 1 \tag{1}$$

where n is $S \times Q$ matrix of net input (column) vectors and returns each element of N squashed between-1 and 1; S - Number of neurons; Q - Number of input vectors.

Testing and Validation

The Mean Squared Error (MSE) and coefficient of correlation between the predicted and measured values were taken as the performance criterion of the network. The MSE was calculated as Eq. (2):

$$MSE = \frac{1}{N}\sum_{N}(d-0)^2$$

where d, O, and N represent the predicted output, the measured output, and the number of input-output data pairs, respectively.

The prediction was based on the input data sets shown above. In this study, eight models were run for each section. The quality of the results obtained for the models is presented in Table 4. The errors suggest that the network with a 3-4-1 architecture is the optimum for both Section 1 and 2. This network is shown in Figure 2.

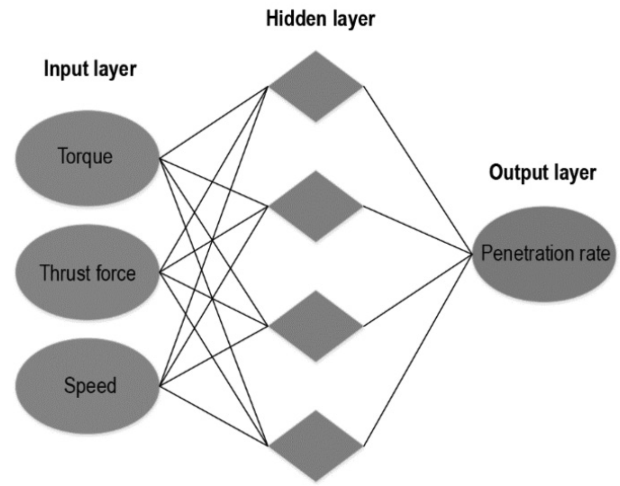

Figure 2: Suggested ANN for predicting the ROP.

Results and Discussion

Figure 3 shows graphs comparing the measured and predicted data for the considered ANN models for, respectively, Sections 1 and 2. It appears that the models have predicted ROP (rate of penetration) values close to the measured one in situ. The correlation coefficients between measured and predicted are close to 1.

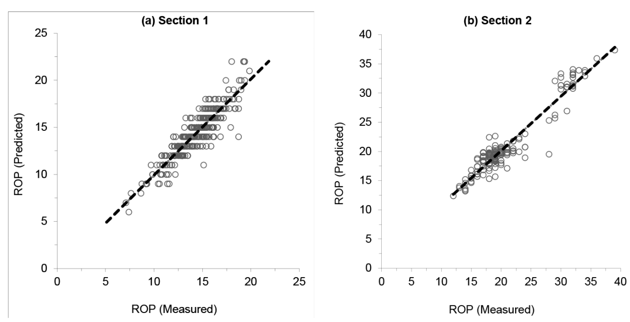

Figure 3: Correlation between measured and predicted ROP: (a) Section 1 and (b) Section 2.

Table 4: Comparison between some of the models

Model	*MSE (training)*		*MSE (cross-validation)*		*MSE (test)*		*R (test)*	
	S1	*S2*	*S1*	*S2*	*S1*	*S2*	*S1*	*S2*
3-3-1	1.368	3.572	0.865	4.275	1.666	4.320	0.90388	0.94453
3-4-1	1.265	2.572	1.160	1.636	0.975	1.734	0.92408	0.9556
3-5-1	1.057	3.479	1.762	3.012	1.615	2.793	0.88663	0.97599
3-6-1	1.047	2.982	1.974	1.701	1.320	3.329	0.90958	0.93839
3-7-1	1.224	3.978	1.494	3.260	1.226	3.898	0.88829	0.95103
3-5-3-1	1.116	4.416	1.142	3.868	1.566	5.329	0.90567	0.90094
3-7-7-1	1.429	2.995	1.665	5.359	1.844	3.593	0.84812	0.90863
3-7-5-1	1.588	3.862	1.075	2.59	1.337	4.01	0.91577	0.90997

The results obtained from the ANN modeling show that the estimated ROP are reliable, accurate, and close to the real machine performance for both the studied sections. Measured and estimated penetration rates are compared for each section where data was collected (see Figures 4 and 5).

Two ANN models were designed using neural networks for each section to check the device's

Table 5: Input parameters values

No.	*Torque (MN.m)*	*Thrust Force (MN)*	*Speed (mm/min)*	*Penetration Rate (mm/rot)*	
				S1	*S2*
1	6.1	27.8	27	14.94	20.02
2	5.5	28.1	29	15.98	20.57
3	5	26.2	28	15.20	18.48
4	4.4	25.2	25	13.64	16.31
5	4	28.4	20	10.74	14.25
6	3.3	17	19	11.75	12.52
7	5.7	28	30	16.48	21.66
8	4.9	20	29	15.71	17.45
9	3.8	28	31	17.39	26.20
10	5.95	31.1	36	17.46	34.94
11	4.7	23.5	24	12.89	15.44
12	5.3	26.3	23	12.32	15.61
13	4.7	23.5	24	12.89	15.44
14	5.3	26.3	23	12.32	15.61
15	3.6	26.2	26	14.19	17.07
16	3.7	25.5	19	10.58	13.31
17	4.3	26.8	28	15.65	18.33
18	5.6	26.7	28	15.49	19.29
19	5.3	26.7	21	11.21	14.57
20	5.3	30.8	20	10.87	15.27
21	4.1	19.	22	11.49	13.71
22	4.1	16	24	12.52	14.25
23	4.3	19	22	11.41	13.67
24	4.3	18	22	11.37	13.52
25	3.8	25	28	15.45	17.89
26	4	23	28	15.42	17.52
27	3.8	23	28	15.34	17.54
28	4.4	23	29	16.07	18.03
29	4	22	33	18.17	19.81
30	3.9	21	35	18.98	20.52

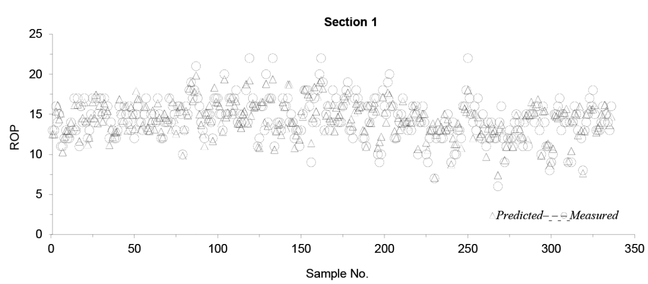

Figure 4: Comparison of measured and predicted ROP for Section 1.

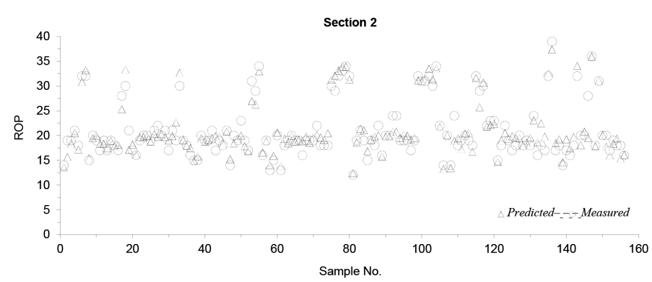

Figure 5: Comparison of measured and predicted ROP for Section 2.

penetration rate. As previously described, the difference between the two sections is only in the type of cutting tools used for the excavation. Table 5 shows a series of data where the input parameters, namely torque, force, and velocity, are gathered. This data set contains very low to very high input values. This data was used to train the neural networks for the two considered sections. The output data obtained is also given for a precise comparison between the two sections.

The results show that increasing the input parameters values of Section 1 induces a very low penetration rate increase. For example, the torque, thrust force, and speed are, respectively, equal to 6.1 MN.m, 27.849 MN, and 27 mm/min (large values), and the penetration rate is only equal to 19.14 mm/rot. By comparing the results obtained for these two sections, with the same input parameters increase in each section, the penetration rate obtained from the model of Section 2 has a faster growth rate than the one of Section 1. On average, the penetration rate in Section 2 is estimated to be 30% higher than in Section 1, with the same values of input parameters.

Conclusion

By expanding the application of EPB-TBMs to the excavation of tunnels in soft soils, the performance of this kind of machine becomes a significant issue. By considering new modeling techniques, the functional parameters of these machines can be calculated with high precision. This research studied the efficiency of two types of cutting tools (disk cutter and ripper) in silty-clay soils. These sections have the same geotechnical parameters, and only the TBM's parameters were modeled by artificial neuron networks. The penetration rate is taken as the output parameter for comparison. The artificial neural network is used to predict the penetration rate for the two sections. The input parameters of the ANN are the thrust force, torque, and speed of the TBM machine. The penetration rate's predictive values permitted selecting the appropriate cutting tools for excavation in silty-clay soils. A data set for the simulations was considered to train the neural networks (one network for each section), and the following results have been obtained.

- Based on the evaluations, it was observed that the best-predicted value obtained from the ANN was obtained with one hidden layer that contains four neurons.
- The predicted penetration rate values were so close to the measured values, and the correlation coefficients were more than 0.95. So, the estimated ROP is reliable and close to the actual machine performance for both the studied sections.
- According to the results, by increasing the input parameters values, the penetration rate of Section 2 has a faster growth rate than Section 1; considering the performance parameter observed in silty soils, the performance of the ripper is better in comparison with the disc cutter one.

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