**Geomechanics and Engineering**, *Vol. 37, No. 3 (2024) 197-211*
https://doi.org/10.12989/gae.2024.37.3.197

# EPB-TBM performance prediction using statistical and neural intelligence methods

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(*Received July 6, 2022, Revised Marh 22, 2024, Accepted March 23, 2024*)

**Abstract.** This research studies the effect of geotechnical factors on EPB-TBM performance parameters. The modeling was performed using simple and multivariate linear regression methods, artificial neural networks (ANNs), and Sugeno fuzzy logic (SFL) algorithm. In ANN, 80% of the data were randomly allocated to training and 20% to network testing. Meanwhile, in the SFL algorithm, 75% of the data were used for training and 25% for testing. The coefficient of determination ($R^2$) obtained between the observed and estimated values in this model for the thrust force and cutterhead torque was 0.19 and 0.52, respectively. The results showed that the SFL outperformed the other models in predicting the target parameters. In this method, the $R^2$ obtained between observed and predicted values for thrust force and cutterhead torque is 0.73 and 0.63, respectively. The sensitivity analysis results show that the internal friction angle (φ) and standard penetration number (SPT) have the greatest impact on thrust force. Also, earth pressure and overburden thickness have the highest effect on cutterhead torque.

**Keywords:** artificial neural network; fuzzy logic; geotechnical parameters; multivariate linear regression; soft ground tunneling

## 1. Introduction

Performance prediction is the most important factor in mechanized excavation using tunnel boring machines (TBMs). The economics of a tunneling project is normally associated with performance activities, and its success is a function of the project's scheduled cost and progress rate. For the project to succeed, the planning process must be based on realistic conditions of the boring machine performance, reflecting known and unknown factors. In this regard, several models have been developed to estimate the performance of the TBM, mainly using geological and geotechnical data (Avunduk and Copur 2018).

Mahmoodzadeh *et al.* (2022) studied several models for tunnel boring machine performance prediction based on machine learning. Li *et al.* (2022) developed a hybrid ELM-LSO model to predict the advance rate of TBM in hard rock. Lin *et al*. (2022) proposed a hybrid model for shield movement performance prediction based on a particle swarm optimization (PSO) algorithm and a long short-term memory (LSTM) neural network. Wang *et al.* (2021) presented a prediction model for rock-burst in hard rock mines using tree-based ensemble techniques. In another study, Zeng *et al*. (2022) propped several hybrid learning machine techniques for TBM performance prediction.

Parameters affecting the performance of mechanical excavation systems can be divided into three main groups, including geological and geotechnical, mechanical (machine-based), and operational and environmental factors (Kim *et al.* 2020, Copur *et al*. 2014, Herrenknecht and Bappler 2007, Lovat and Eng 2007). After geological studies and selecting the tunnel route, the TBM should be chosen in such a way that its operation parameters (i.e., cutterhead torque, power, and thrust force) are optimal based on the geological and geotechnical conditions (Bilgin and Algan 2012, Marinos *et al*. 2008). Yagiz (2008) performed a statistical analysis of data from the Queens Tunnel excavated in New York. Based on the results, the author proposed an empirical model to predict the penetration rate of TBM. This researcher attributed four rock mass parameters (i.e., uniaxial compressive strength, Block Punch Index, spacing, and joints' orientation) to the TBM's penetration rate.

To our knowledge, there are limited studies on predicting the performance of earth pressure balance TBMs (EPB-TBMs). For instance, Bilgin and Algan (2012) proposed an experimental model for predicting the instant penetration rate of EPB-TBMs, which are used in the semi-closed mode for rock excavation. Shi *et al.* (2011) offered a theoretical model for predicting cutterhead torque and thrust force of TBMs on soft grounds. Kasper and Meschke (2004) applied three-dimensional numerical simulation models to estimate the thrust force of EPB TBMs. Also, Ates *et al.* (2014) proposed experimental models to determine the characteristics of different types of soft and hard rock TBMs based on a large database. Zhang *et al.* (2015) provided mathematical models for predicting the cutterhead torque and advance rate of EPB TBMs. Avunduk and Copur (2018) investigated the effect of soil parameters

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http://www.techno-press.org/?journal=gae&subpage=7
ISSN: 2005-307X (Print), 2092-6219 (Online)

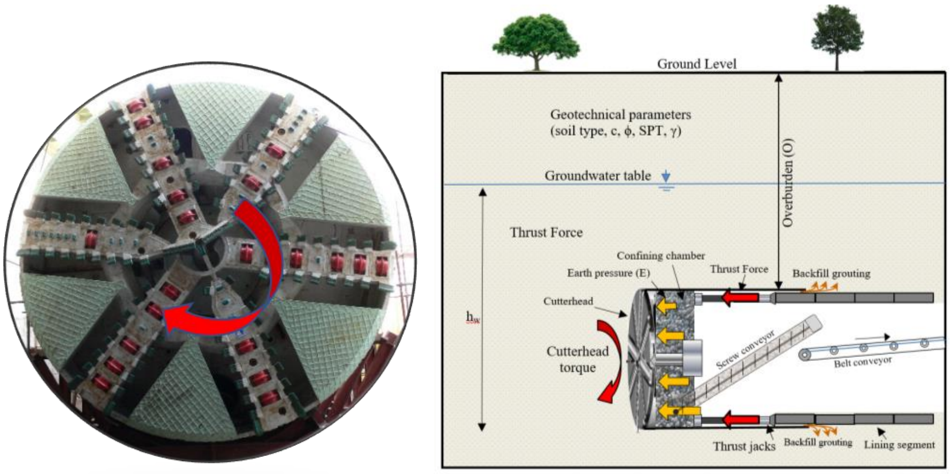

Fig. 1 The 6.88-m-diameter EPB-TBM cutterhead of Tabriz Metro Line-1 (left) and schematic diagram for different parameters in EPB-TBM tunneling

Table 1 Technical specifications of the TBM of Tabriz Metro Line-1 (Barzegari *et al*. 2018)

| TBM Type | Diameter (m) | Cutterhead Opening Ratio (%) | Length of Shield (m) | Max. Thrust (kN) | Max. Torque (kN.m) | Cutterhead Speed (rpm) |
|---|---|---|---|---|---|---|
| EPB | 6.88 | 31 | 9.925 | 44,080 | 8960 | 0 to 4 |

on the performance of EPB-TBMs used in the Ayvali water conveyance tunnel project in Istanbul, Turkey. These researchers prepared simple and multivariate linear regression models by combining laboratory experiments and real TBM data. As a result, they proposed some relationships based on soil geotechnical parameters to predict instantaneous cutting rates, cutterhead torque, thrust force, and specific energy. Elbaz *et al*. (2019) predicted the advance rate of EPB-TBM using ground parameters (i.e., overburden thickness and earth pressure) and slurry injection pressure. To this end, they applied adaptive neural-fuzzy inference system (ANFIS) and genetic algorithm (GA) methods. Darbor *et al.* (2020) explored the effect of geotechnical parameters (i.e., cohesion, internal friction angle, and shear modulus) and machine parameters (i.e., thrust force, cutterhead torque, and rotational speed of the cutterhead) on the penetration rate of EPB-TMB in Tabriz Metro Line-2. The predictions were made using linear regression methods, Sugeno fuzzy logic (SFL), Mamdani fuzzy logic (MFL), and neuro-fuzzy. Based on the results of these researchers, the neuro-fuzzy method shows a more accurate prediction of the penetration rate of the TBM. Overall, the cutterhead torque of the boring machine and the internal friction angle have the highest and lowest effects on the penetration rate, respectively. Qin *et al.* (2020) used a novel hybrid deep neural network to predict cutterhead torque for shield tunneling machines precisely.

This study investigates the effect of environmental and geotechnical parameters on the thrust force and cutterhead torque of EPB-TBMs in Tabriz Metro Line-1. Despite previous studies on predicting the performance of TBMs in hard rocks, soft ground TBMs have been less investigated, especially for EPB-TBMs. The present study has some novelties regarding database and studied parameters, geological conditions, and research methods and can be very useful in advancing similar studies.

## 2. Case study and data collection

A practical tunneling project in Tabriz, Iran, was considered the case study for investigating the performance of EPB TBM. Tabriz Metro Line-1 is one of the urban train routes of the Tabriz subway network. This route is 17.2 km long and includes 18 stations. About 8 km of the route is implanted in the city's downtown in the form of deep twin tunnels. The groundwater level in the tunnels varies from 2.5 to 23 m, and the tunnel overburden varies from 7 to 25 m. Excavations were performed using two shielded EPB-TBM. The length of each tunnel, considering the stations, is 8.07 km. The bored diameter of the tunnels is 6.88 m, and their ultimate diameter after installing the concrete segment is 6 m (Barzegari *et al*. 2014). Some technical specifications of the TBMs used in Tabriz Metro Line-1 are detailed in Table 1. The EPB-TBM cutterhead and investigated parameters are presented in Fig. 1.

To conduct engineering geology studies of the tunnels in Tabriz Metro Line-1, 85 boreholes were drilled using a rotary drilling machine using a continuous core extraction method. The depth of the boreholes varies from 30 to 50 m. Also, the physical and mechanical properties of geological layers were determined in all boreholes by performing in-situ and laboratory tests on soil samples. The geotechnical characteristics of the studied alluvium deposits are briefly presented in Table 2 (Barzegari and Uromeihy 2016).

In this study, analyses were performed using effective parameters on TBM performance. Variables used for this purpose are the results of the standard penetration number (SPT), groundwater level ($h_w$), soil gradation, unit weight, cohesion (c), and internal friction angle (φ). The variation range of these parameters by soil type is presented in Table 3. Overburden (O) and confining chamber earth pressure (E) are also considered independent parameters during the research.

Table 2 Geotechnical characteristics of Tabriz Metro Line-1 (Barzegari and Uromeihy 2016)

| Test | Parameters | | Results |
|---|---|---|---|
| Field tests | Standard Penetration Number (N) | | Very loose to very dense; in some cases, layers with low SPT |
| | In-Site permeability (cm/s) | | $10^{-2}$-$10^{-6}$ |
| | Groundwater level (m) | | 2.5-23 |
| Laboratory tests | Unified soil classification | | In the order of frequency, including SP-SM, SW-SM, SW and GP, and in some cases GP-GM, GW-GM, CL, and ML |
| | Moisture content (%) | | 13–16 |
| | Unit weight (kN/m$^3$) | | Wet unit weight: 12.8-23<br>dry unit weight: 10-19 |
| | Uniaxial strength (kPa) | | 70-480 |
| | Direct shear | φ (degree) | Gravelly layers: 31; Sandy layers: 34; silty layers: 25-35 |
| | | c (kPa) | 0–40 |
| | Triaxial strength | φ (degree) | Sandy samples: 29-41<br>silt-clayey samples: 4-8 |
| | | c (kPa) | Undrained cohesion of sand samples: 0-16<br>silty-clay samples: 29-40 |

Table 3 Engineering geology characteristics based on the soil type of Tabriz Metro Line-1

| Soil class. | unit weight (kN/m$^3$) | Cohesion (kPa) | Internal friction angle (degree) | Earth pressure balance (kPa) | SPT (N) |
|---|---|---|---|---|---|
| GP | 18.2-19.8 | 0-0.01 | 27-30 | 37-42 | 33-65 |
| GP-GM | 19.6-26.45 | 0-3 | 25.5-36 | 89-105 | 24-31 |
| GM | 16.4-18.5 | 0-0.03 | 30-32 | 34-51 | 11-17 |
| GC | 26.3-26.9 | 4-6 | 32-34 | 103-117 | 20-36 |
| SP | 17.62-20 | 1-9 | 29-38 | 98-105 | 32-55 |
| SW-SM | 17-19.8 | 0.3-12 | 28.33-39 | 42-106 | 29-65 |
| SP-SM | 18-26.5 | 0-16 | 27-40 | 33-134 | 22-87 |
| SP-SC | 26.3-26.8 | 1-8 | 28-31.5 | 108-134 | 48-74 |
| SM | 17-26.65 | 0-40 | 27-41 | 30-129 | 16-99 |
| SC | 19-27.05 | 0-30 | 25.5-33.5 | 41-132 | 11-68 |
| SC-SM | 18.5-26.6 | 0-9 | 27-36 | 35-132 | 25-64 |
| ML | 19-20.5 | 2-35 | 31-35 | 88-101 | 28-44 |
| CL | 19-27 | 6-14 | 26-31 | 40-83 | 23-33 |

Table 4 Weighting of different soil along the tunnel route

| Group | 1 | 2 | 3 | | | | | | 4 | 5 | 6 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Soil class | SM | SC | SP-SM | SP-SC | SC-SM | SW-SM | SP | GP-GM | ML | CL | GP | GM | GC |
| Weight | 4 | 6 | 7 | 7 | 3 | 5 | 8 | 9 | 2 | 1 | 9 | 9 | 9 |

Since the soil type is a qualitative parameter, it is necessary to convert the soil type into a quantitative parameter when using this parameter in statistical studies and artificial intelligence. For this purpose, first, the soils were divided into 6 groups according to their abundance in the tunnel route. Next, a specific weight between 1 and 10 was assigned to each soil type based on their possible impact on thrust force and cutterhead torque, such that coarse-grained soils had more weight while fine-grained soils had less weight. The group and weight of each soil type in the tunnel route are presented in Table 4. In this process, if a certain section of the tunnel is composed of several different soil types, the average weight can be easily determined based on each soil layer’s thickness and weight.

The statistical distribution of the input parameters is detailed in Table 5. Fig. 2 shows the scatterplot matrix and correlation coefficient of input and output parameters. Meanwhile, the frequently distribution and histogram for each parameter are depicted on the diagonal. According to this figure, some input parameters have a direct relationship with each other, and some others have an inverse relationship. In addition, thrust force and cutterhead torque serve as target data.

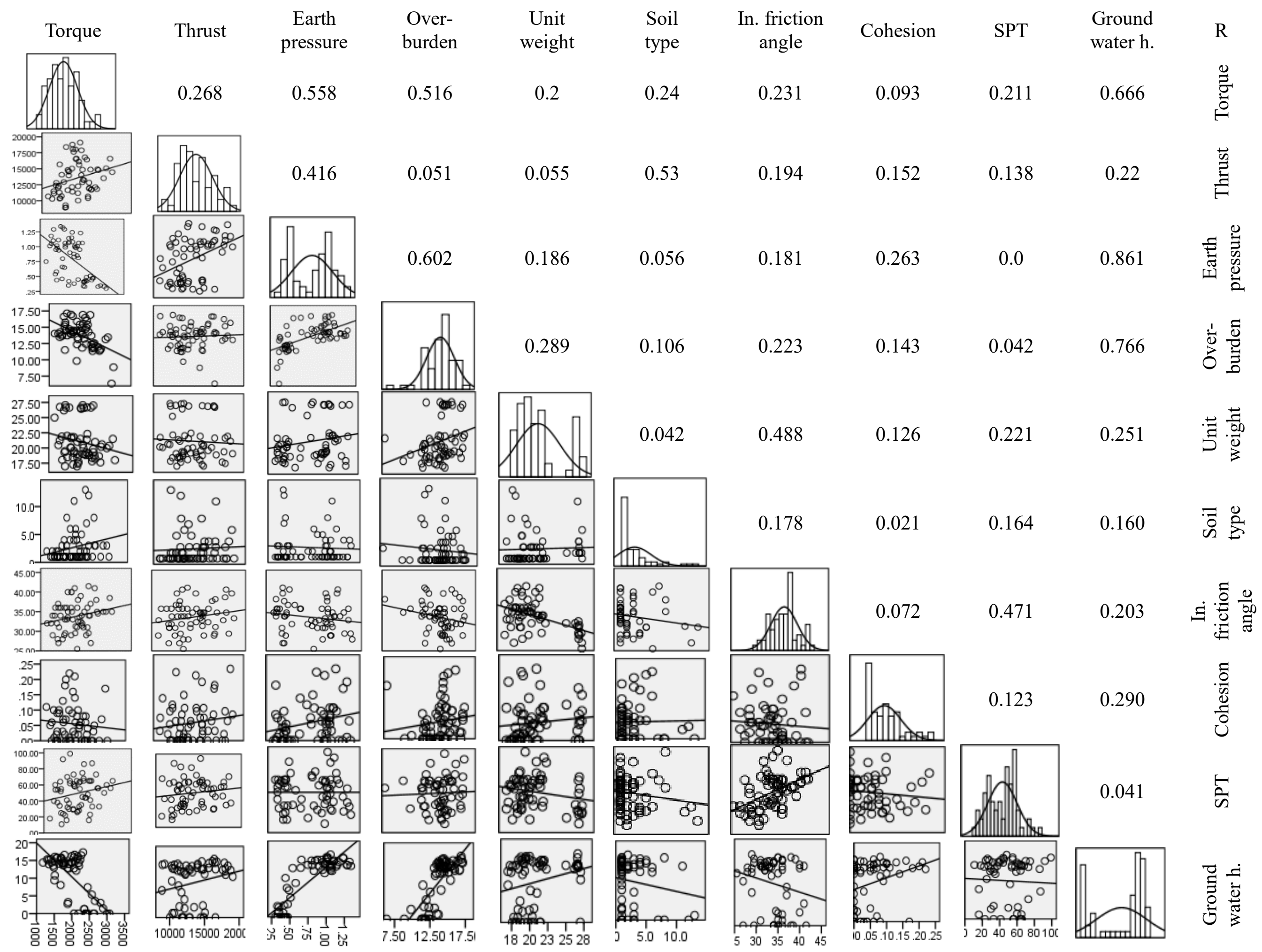

Fig. 2 Scatterplot matrix and correlation coefficient between the input and output parameters

Table 5 Detailed statistical distribution of the input parameters

| Parameter | Min. | Max. | Mean | Std. deviation | Median | Skewness | Kurtosis |
|---|---|---|---|---|---|---|---|
| Torque (kN.m) | 1181 | 3069.80 | 2009.51 | 444.26 | 2002.5 | 0.34 | -0.43 |
| Thrust force (kN) | 8891.5 | 19086 | 13498.4 | 2336.95 | 12925.5 | 0.35 | -0.75 |
| Earth pressure (kPa) | 30 | 134 | 79.21 | 32.5 | 88 | -9.0 | -14.7 |
| Internal friction angle (degree) | 25.5 | 41 | 33.78 | 3.747 | 34.0 | 0.03 | -0.41 |
| Cohesion (kPa) | 0.0 | 40 | 6.28 | 9.11 | 4 | 2.28 | 5.46 |
| SPT | 11 | 99 | 49.524 | 20.085 | 54 | 0.15 | -0.51 |
| Soil type | 1.0 | 9 | 2.698 | 2.768 | 1.0 | 2.19 | 4.71 |
| Grand water head (m) | 17 | 25.05 | 10.287 | 6.363 | 13.93 | -0.74 | -1.21 |
| Overburden (m) | 6.37 | 17.14 | 13.779 | 2.007 | 14.03 | -0.91 | 2.08 |
| Unit weight (kN/m$^3$) | 17 | 27.05 | 21.004 | 3.149 | 20 | 0.91 | -0.47 |

## 3. Methodology

The development of experimental models using soil parameters can provide valuable data in the feasibility stage of a tunneling project and the initial design of an EPB-TBM based on geotechnical parameters. Therefore, the operating and performance parameters of EPB-TBM (thrust force and cutterhead torque) were used in statistical analysis and neural networks to obtain the relationships between the geotechnical parameters. The flowchart of this present research process is available in Fig. 3. In this study, a simple regression analysis was first carried out using Microsoft Excel software. Next, the multivariate linear regression analysis using the most appropriate subsets was

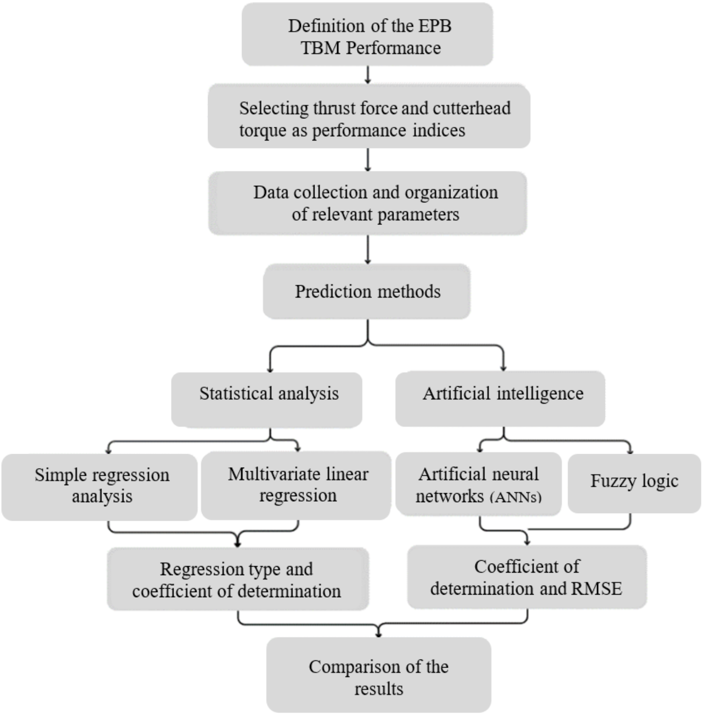

Fig. 3 Flowchart of the research process

performed in the SPSS environment. Data preparation for the modeling process using artificial neural network (ANN) is done in two stages: data normalization in the range of 0 to 1 and dividing the data into two categories of training and testing (Alvisi *et al.* 2006). One of the reasons for normalizing the input data in the range of 0 to 1 is the need for transfer functions (such as the sigmoid function) as they cannot distinguish between very large values. Besides, data normalization simplifies the process because the outputs and inputs of all subsequent layers are also in the range of 0 to 1 (Demuth *et al.* 1992). A key issue in ANN models is determining the appropriate percentages of data at each modeling stage and the number of intermediate nodes (Lallahem *et al.* 2005). Choosing the structure of the ANNs is a very difficult and important task that requires selecting the optimal number of layers and the optimal number of neurons in each layer. There is no specific method for determining the optimum network. It is generally suggested to determine the number of neurons in each layer by keeping the number of layers constant (Menhaj 2012). However, some researchers believe that many problems can be solved using a middle (hidden) layer (Basheer 2000).

The basics of fuzzy logic were first presented by Lotfi Zadeh (1996). Later, he presented his ideas for a concept called linguistic variables – as a variable defined in a fuzzy set. In fact, evolved fuzzy logic is classical logic, except that fuzzy logic, unlike classical logic, has no definite boundaries. In other words, in these sets, the membership of an element to the set is not a true (one) or false (zero) statement, but there is a spectrum of answers. Therefore, an element in fuzzy sets, in addition to the above two propositions, can have answers between 0 and 1 (Nadiri 2013). In this study, for the artificial neural network, 80% of the data were randomly allocated to training and 20% for testing the network and in the fuzzy logic model, 75% of the data were used for training and 25% for testing.

### *3.1 Statistical analysis*

### *3.1.1 Simple regression analysis*

Simple regression is the simplest form of regression analysis consisting of independent and dependent variables. In this study, regression analysis was performed to extract the relationships between TBM parameters (i.e., thrust force and cutterhead torque) with geotechnical and environmental properties (i.e., unit weight, cohesion, internal friction angle, SPT, overburden, water height from the tunnel floor, and chamber earth pressure). The regression results between these parameters and thrust force are presented in Table 6.

Table 6 shows that the correlation between the thrust force and each geotechnical factor is less than 0.1965. As can be seen, there is a poor relationship between geotechnical parameters and thrust force, indicating that thrust force cannot be calculated using simple regression. The highest coefficient of determination ($R^2$) between thrust force and input parameters is related to confining chamber earth pressure (E) ($R^2 = 0.1965$). This pressure is calculated based on a set of parameters, including depth, unit weight, internal friction angle, cohesion, and groundwater level.

The regression results obtained between the geotechnical parameters and the cutterhead torque of the TBM are presented in Table 7.

Table 7 shows the correlation between each independent variable and the boring machine’s total cutterhead torque is less than 0.4795. Here, the lowest correlation is related to cohesion with a linear relationship, and the highest is related to water height from the tunnel invert with a polynomial relationship. Among other parameters, unit

Table 6 Relationships between independent variables and thrust force

| Independent variables | Relationship | Regression Type | $R^2$ |
|---|---|---|---|
| Wet unit weight ($\gamma$) ($kN/m^3$) | $Th = -46.007(\gamma) + 14465$ | Linear | 0.0025 |
| | $Th = -1021\ln(\gamma) + 16597$ | Logarithmic | 0.0031 |
| | $Th = 14242e^{-0.003(\gamma)}$ | Exponential | 0.0031 |
| | $Th = 1.1947(\gamma)^2 + 99.5(\gamma) + 15050$ | Polynomial | 0.0034 |
| | $Th = 16783(\gamma)^{-0.078}$ | Power | 0.0033 |
| Overburden (O) (m) | $Th = 66.387(O) + 12584$ | Linear | 0.0026 |
| | $Th = 354.47\ln(O) + 12573$ | Logarithmic | 0.0005 |
| | $Th = 12733e^{0.0029(O)}$ | Exponential | 0.0009 |
| | $Th = 53.273(O)^2 - 1307.7(O) + 21192$ | Polynomial | 0.0224 |
| | $Th = 13119(O)^{0.0038}$ | Power | 1E-05 |
| Groundwater height ($h_w$) (m) | $Th = -80.405(h_w) + 14373$ | Linear | 0.0483 |
| | $Th = 12446e^{0.0061(h_w)}$ | Exponential | 0.0393 |
| | $Th = 21.437(h_w)^2 - 252.57(h_w) + 12974$ | Polynomial | 0.0752 |
| SPT (N) | $Th = 18.078(N) + 12603$ | Linear | 0.019 |
| | $Th = 1187.9\ln(N) + 8978.1$ | Logarithmic | 0.0453 |
| | $Th = 12308e^{0.0015N}$ | Exponential | 0.0235 |
| | $Th = -1.4658(N)^2 + 167.65(N) + 9372.9$ | Polynomial | 0.0891 |
| | $Th = 9216.1(N)^{0.0954}$ | Power | 0.0534 |
| Cohesion (c) (kPa) | $Th = -1981.2(c) + 13623$ | Linear | 0.0047 |
| | $Th = 13416e^{-0.2C}$ | Exponential | 0.0087 |
| | $Th = -36920(c)^2 + 10100(c) + 13311$ | Polynomial | 0.0311 |
| Internal friction angle ($\varphi$) (Degree) | $Th = 119.43(\varphi) + 9533.4$ | Linear | 0.0263 |
| | $Th = 3733.3\ln(\varphi) + 444$ | Logarithmic | 0.0236 |
| | $Th = 9839.7e^{0.009\varphi}$ | Exponential | 0.0271 |
| | $Th = 25.884(\varphi)^2 - 1609.6(\varphi) + 38080$ | Polynomial | 0.0482 |
| | $Th = 4946.7(\varphi)^{0.2817}$ | Power | 0.0245 |
| Earth pressure (E) (kPa) | $Th = 3374.2(E) + 10833$ | Linear | 0.1734 |
| | $Th = 2128.6\ln(E) + 14212$ | Logarithmic | 0.1434 |
| | $Th = 10942e^{0.2422E}$ | Exponential | 0.1633 |
| | $Th = 5185(E)^2 - 4667.8(E) + 13410$ | Polynomial | 0.1965 |
| | $Th = 13939(E)^{0.1517}$ | Power | 0.1331 |

weight, internal friction angle, and SPT correlate poorly. In contrast, the earth pressure of the confining chamber (E) and overburden correlates relatively well with the cutterhead torque of the boring machine. All the extracted relationships between the geotechnical properties and machine's cutterhead torque are positive correlations, indicating that the cutterhead torque increases with increasing each parameter.

### *3.1.2 Multivariate linear regression*

Multivariate linear regression analysis is used to obtain the best relationship between variables when input parameters are more than one. In general, the multivariate linear regression method produces a relationship between input (independent) and output (dependent) variables. This method provides better results in analyses with constant conditions because it allows controlling many other factors that simultaneously affect the dependent variable. Eq. (1) presents the general model for linear multivariate linear regression analysis

$$Z = a + bX + cY + \ldots \tag{1}$$

Where $Z$ is the dependent variable, $X$ and $Y$ are independent variables, and b and c are constants of X and Y, respectively. Multivariate linear regression was performed using the SPSS software. For this purpose, geotechnical and environmental parameters, including cohesion, internal friction angle, unit weight, overburden thickness, groundwater depth, SPT, and confining chamber pressure (E), were considered as independent parameters, and TBM performance parameters, including thrust force and cutterhead torque as dependent variables to predict the performance of EPB-TBM.

There are several regression models to relate different variables with each other. This study used multivariate regression analysis to examine whether two or more independent variables are related. In the case of multi-linearity, an increase in independent variables may lead to

Table 7 Relationships between independent variables and cutterhead torque

| Independent variable | Relationship | Regression Type | $R^2$ |
|---|---|---|---|
| Wet unit weight (γ) (kN/m³) | $T = -28.269(\gamma) + 2603.3$ | Linear | 0.0402 |
| | $T = -614.9\ln(\gamma) + 3875.3$ | Logarithmic | 0.039 |
| | $T = 2667.6e\text{-}0.015^{(\gamma)}$ | Exponential | 0.0427 |
| | $T = -1.3874(\gamma)^2 + 33.852(\gamma) + 1924.1$ | Polynomial | 0.0408 |
| | $T = 5184.3(\gamma)^{-0.32}$ | Power | 0.0419 |
| Overburden (O) (m) | $T = -114.15(O) + 3582.4$ | Linear | 0.2661 |
| | $T = -1435\ln(O) + 5755.8$ | Logarithmic | 0.2824 |
| | $T = 4007.4e^{-0.052(O)}$ | Exponential | 0.2175 |
| | $T = 10.9(O)^2 - 395.29(O) + 5343.6$ | Polynomial | 0.2954 |
| | $T = 10675(O)^{-0.649}$ | Power | 0.2288 |
| Groundwater height ($h_w$) (m) | $T = -46.536(h_w) + 2488.2$ | Linear | 0.4442 |
| | $T = 2467.2e^{-0.022(h_w)}$ | Exponential | 0.4041 |
| | $T = 4.1363(h_w)^2 + - 112.84(h_w) + 2567.8$ | Polynomial | 0.4795 |
| SPT (N) | $T = 4.6621(N) + 1778.6$ | Linear | 0.0444 |
| | $T = 229.94\ln(N) + 1134.5$ | Logarithmic | 0.0598 |
| | $T = 1740.8e^{0.0024N}$ | Exponential | 0.047 |
| | $T = -0.1698(N)^2 +21.987(N) + 1404.5$ | Polynomial | 0.0776 |
| | $T = 1253.2(N)^{0.1177}$ | Power | 0.0621 |
| Cohesion (c) (kPa) | $T = 167.23(c) + 1999$ | Linear | 0.0012 |
| | $T = 1946.4e^{0.1216C}$ | Exponential | 0.0025 |
| | $T = 4335(c)^2 - 1251.3(c) + 2035.6$ | Polynomial | 0.014 |
| Internal friction angle (φ) (Degree) | $T = 29.314(\varphi) + 1036.3$ | Linear | 0.0558 |
| | $T = 947.15\ln(\varphi) - 1302.5$ | Logarithmic | 0.0534 |
| | $T = 1237.6e^{0.0139\varphi}$ | Exponential | 0.0495 |
| | $T = 1.8264(\varphi)^2 - 92.691(\varphi) + 3050.6$ | Polynomial | 0.0597 |
| | $T = 413.92(\varphi)$ | Power | 0.0467 |
| Earth pressure (E) (kPa) | $T = -760.97(E) + 2610.6$ | Linear | 0.3107 |
| | $T = -564.1\ln(E) + 1820.5$ | Logarithmic | 0.3548 |
| | $T = 2605.2e^{-0.359E}$ | Exponential | 0.2745 |
| | $T = 1346.3(E)^2 - 2849.1(E) + 3279.7$ | Polynomial | 0.3656 |
| | $T = 1794.3(E)^{-0.266}$ | Power | 0.3118 |

faulty results. Tolerance and variance inflation factor (VIF) are among the most common tools for finding the degree of multi-linearity (Avunduk and Copure 2018). Regression reliability declines when the variance inflation coefficient is greater than 10 (Jammalamadaka 2003). The tolerance values are from 0 to 1, with lower values suggesting a strong relationship between the (independent) predictor variables. Also, when tolerance is around 0.4, the situation is not risky, but when it is 0.1, it is problematic. The closer the value of the tolerance parameter is to 1, the lower the probability of collinearity (Meyers *et al*. 2016). Therefore, regression models with VIF < 10 and tolerance in the range of 0.6 to 1 were used in this study. The multivariate linear analysis was performed using the backward stepwise regression. In this method, first, all variables are entered into the equation. Then, each parameter is taken out of the equation one by one, in the order of their importance. Based on statistical analyses, the final predictive models for thrust force (Th) and cutterhead torque (T) are obtained according to Eqs. (2) and (3), respectively.

$$\begin{gathered} Th = 3857.634 - 202.714\,(h_w) + 179.160\,(\varphi) + \\ 7163.355\,(E) \qquad (R^2 = 0.309) \end{gathered} \tag{2}$$

$$\begin{gathered} T = 2152.796 - 43.982\,(h_w) + 4.721\,(SPT) + \\ 27.931\,(S) \qquad (R^2 = 0.507) \end{gathered} \tag{3}$$

Where Th and T denote the thrust force (kN) and cutterhead torque (kN), respectively. Also, $h_w$, φ, E, and S indicate the height of groundwater from the tunnel invert (m), internal friction angle (°), EPB (kPa), and soil type, respectively. Table 8 shows the regression models and their coefficients for the independent variables in Eqs. (2) and (3).

Table 9 presents the analysis of variance (ANOVA) results for Eqs. (2) and (3). The F-test analysis is performed by comparing the calculated significance levels (F) with significant F values and using the null hypothesis. According to this hypothesis, if the calculated value of F is greater than its significant value, the null hypothesis is rejected (Gelman and Hill 2006), suggesting that at least

Table 8 Multivariate linear regression coefficients and statistics for Models 2 and 3

| Coefficients | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Dependent variables | Independent Variables | Unstandardized Coefficients | | Standardized Coefficients. | t | Sig. | Collinearity Statistics | |
| | | B | Std. Error | Beta | | | Tolerance | VIF |
| Thrust force | (Constant) | 3857.634 | 2844.584 | | 1.356 | 0.180 | | |
| | Groundwater height | -202.714 | 88.552 | -0.489 | -2.289 | 0.026 | 0.256 | 3.899 |
| | Internal friction angle | 179.160 | 77.767 | 0.255 | 2.304 | 0.025 | 0.959 | 1.043 |
| | Earth pressure | 7163.355 | 1725.449 | 0.883 | 4.152 | 0.000 | 0.259 | 3.866 |
| Torque | (Constant) | 2152.796 | 146.233 | | 14.722 | 0.000 | | |
| | Groundwater height | -43.982 | 6.484 | -0.630 | -6.783 | 0.000 | 0.970 | 1.031 |
| | Soil type | 27.931 | 15.093 | 0.174 | 1.851 | 0.069 | 0.945 | 1.058 |
| | SPT | 4.721 | 2.055 | 0.213 | 2.297 | 0.025 | 0.968 | 1.033 |

Table 9 ANOVA results for Models 2 and 3 in terms of regressions' significance level

| ANOVA | | | | | | |
|---|---|---|---|---|---|---|
| Model | | Sum of Squares | df | Mean Square | F | Sig. |
| 2 | Regression | 133319050.667 | 3 | 44439683.556 | 8.804 | 0 |
| | Residual | 297800228.754 | 59 | 5047461.504 | | |
| | Total | 431119279.421 | 62 | | | |
| 3 | Regression | 6198369.043 | 3 | 2066123.014 | 20.188 | 0 |
| | Residual | 6038352.614 | 59 | 102344.960 | | |
| | Total | 12236721.657 | 62 | | | |

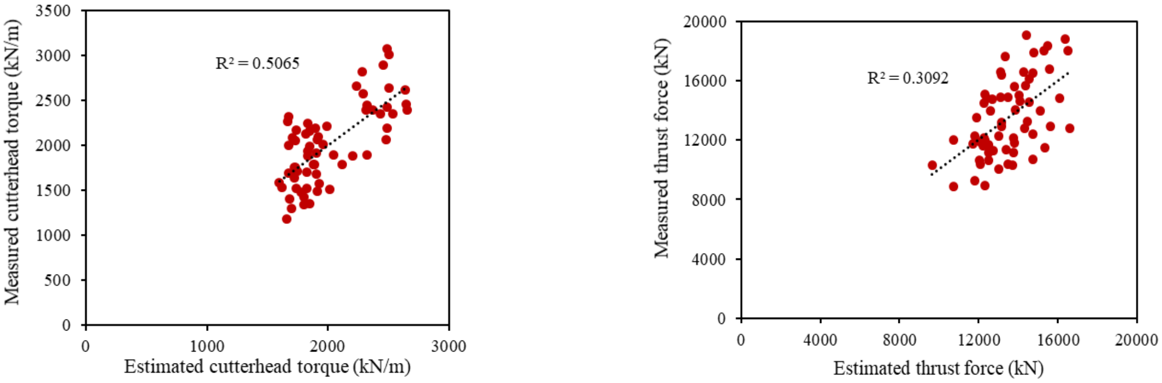

Fig. 4 Comparison of actual and predicted values of thrust force (Right) and cutterhead torque (Left)

one of the independent variables can significantly affect the thrust force and the cutterhead torque of the TBM. Fig. 4 shows the measured values and those predicted using Eqs. (2) and (3) for thrust force and cutterhead torque of the TBM.

### *3.2 Artificial inteligence*

#### *3.2.1 Artificial Neural Networks (ANNs)*

In this study, the thrust force, cutterhead torque, and the parameters affecting them were determined using a feed-forward network with one input layer, two middle layers, and one output layer (see Fig. 5). The transfer functions assigned to the middle and output layers were sigmoid tangent and linear functions, respectively. Since the Bayesian algorithm provides better results than the Levenberg-Marquardt algorithm, it was used for network training. Three neurons in the hidden layer were considered in the networks made for thrust force and cutterhead torque. The thrust force and cutterhead torque were predicted based on eight parameters, including soil type, unit weight, cohesion, internal friction angle, EPB, SPT, overburden, and water height from the tunnel invert as input parameters. As shown in Fig. 6, the $R^2$ between the estimated and actual

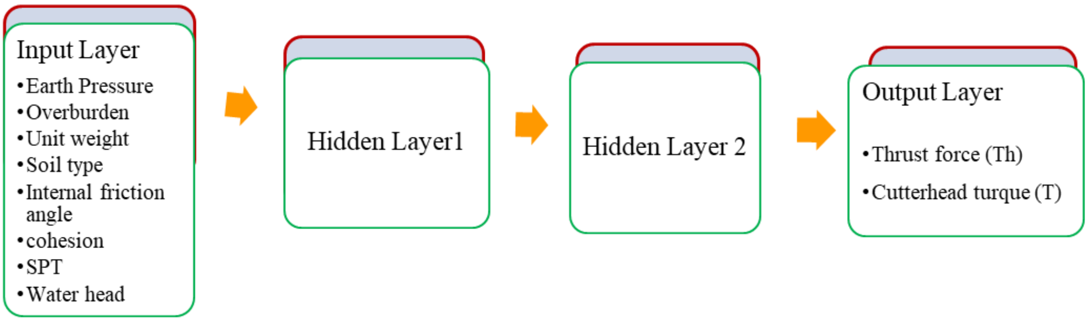

Fig. 5 General structure of artificial neural network in this study

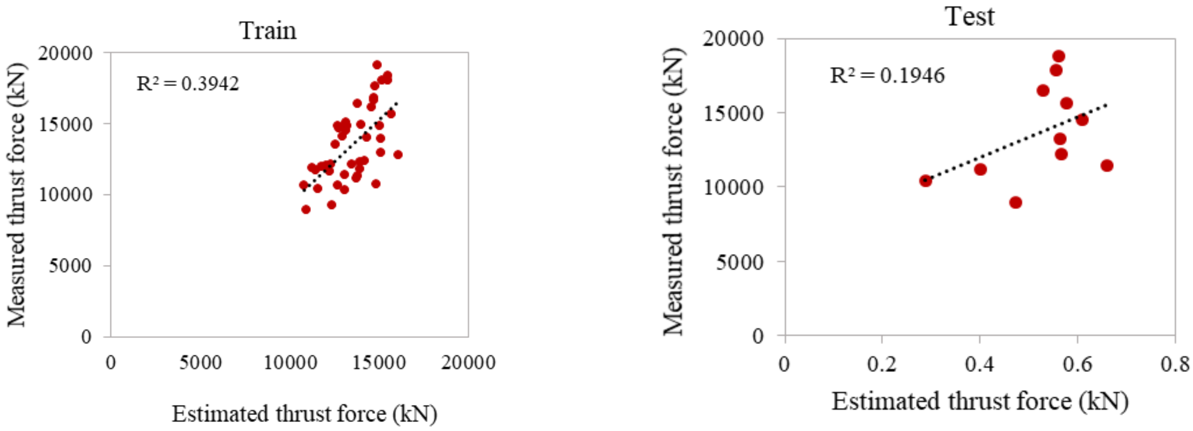

Fig. 6 Comparison of actual and predicted values of the thrust force in training (Left) and test (Right) sets using the ANN

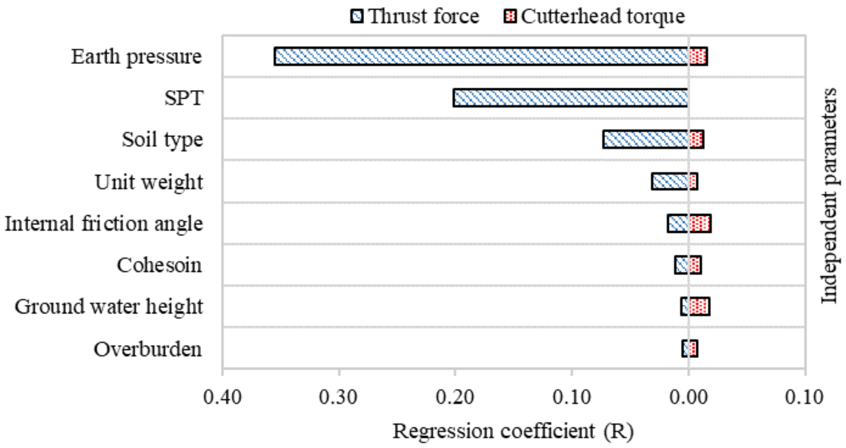

Fig. 7 Diagram of sensitivity analysis for independent parameters against thrust force and cutterhead torque using ANN

values for the training and testing set in the thrust force prediction is 0.3942 and 0.1946, respectively. Also, the root mean square error (RMSE) for each training and test data was 0.1975 and 0.2763, respectively.

In the next step, the effect of each input parameter on the network results was investigated by stepwise removal of each parameter from the set to evaluate its effect on the model. The results of different models made and the sensitivity analysis of the parameters in the form of a Tornado diagram are presented in Fig. 7. According to the sensitivity analysis results, the earth pressure (E) and SPT showed the greatest effect on the thrust force.

Fig. 8 illustrates the estimated and actual values for the training and test data sets in predicting the cutterhead torque using a constructed ANN. The $R^2$ values for training and experimental data were 0.50 and 0.52, respectively. Also, RMSE values for each training and test data are equal to 0.1622 and 0.174, respectively. The effect of each input parameter on the predicted cutterhead torque of the TBM was investigated using the steps performed for the thrust

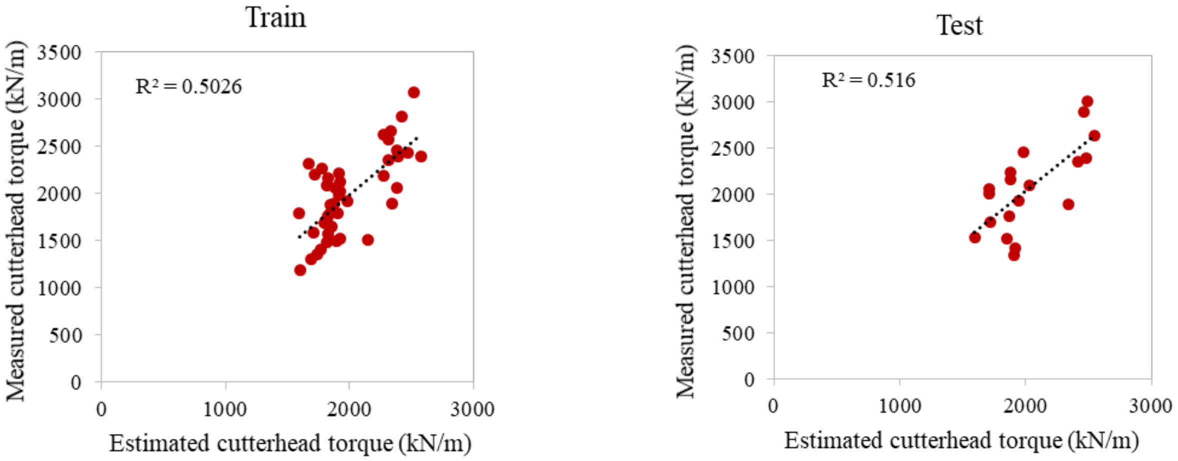

Fig. 8 Comparison of actual and predicted values of the thrust force in training (Left) and test (Right) sets using ANN

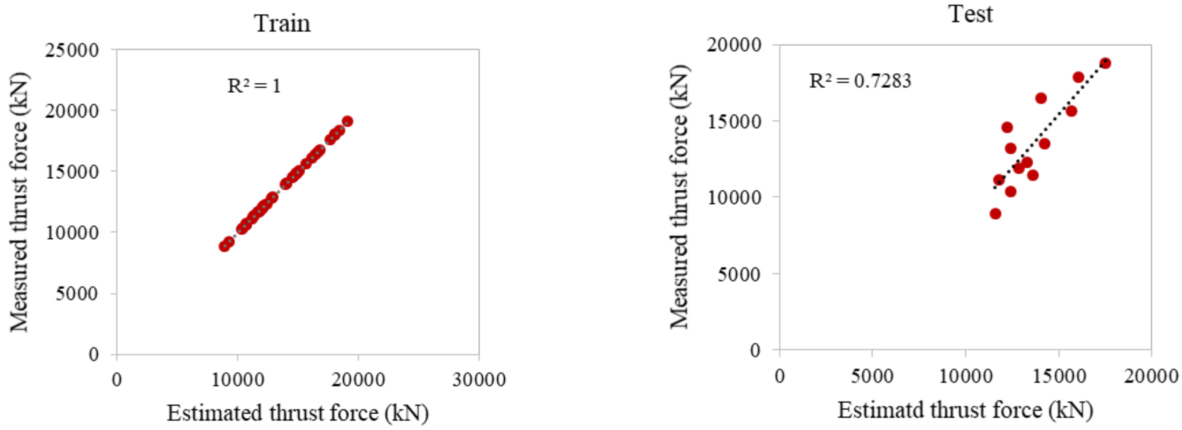

Fig. 9 Comparison of actual and predicted values of thrust force in training (Left) and experimental (Right) sets using Sugeno fuzzy logic (SFL)

force. The results show the negligible effect of each parameter in the predicted models.

### 3.2.2 Fuzzy logic

Each fuzzy system consists of three main steps. The first step, i.e., data fuzzification, is done by defining the membership function. Second, a connection between inputs and outputs is established using a series of rules such as If-Then. In the last step, system outputs are defuzzified based on the output membership function in both Mamdani and Sugeno methods. In the Mamdani method, the membership function is a fuzzy output that must be defuzzified (Mamdani and Assilian 1975). The classification radius is the main factor in determining the categories and if-then rules in the Sugeno fuzzy logic (SFL). The values of this parameter vary between 0 and 1. Increasing this parameter to 1 lowers the number of categories and rules while decreasing it increases the categories and rules (Cho *et al.* 2011). Unlike the Mamdani method, in the Sugeno method, the output function of the fuzzy system output is constant or linear. Among multiple techniques to construct fuzzy logic models, the SFL was used in this paper. Since the output member functions are linear or constant in the SFL, this model is called zero-order or first-order, respectively (Sugeno 1985). The RMSE and $R^2$ are two widely used criteria for evaluating each network's performance and prediction accuracy. These two criteria are calculated using Eqs. (4) and (5)

$$RMSE = \sqrt{\frac{\sum(X_{mea} - X_{pre})^2}{n}} \tag{4}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(X_{mea} - X_{pre})^2}{\sum_{i=1}^{n}(X_{mea} - X_m)^2} \tag{5}$$

where Xmea and Xpre are measured and predicted values, respectively. Xm is the mean value of X, and n is the total number of data sets. Theoretically, the highest precision model has an RMSE of 0 and $R^2$ of 1 (Elbaz *et al.* 2019).

Based on the lowest value of RMSE and the maximum $R^2$, the classification radius for the input and output data was chosen to be 0.47. Figs. 9 and 10 present the models

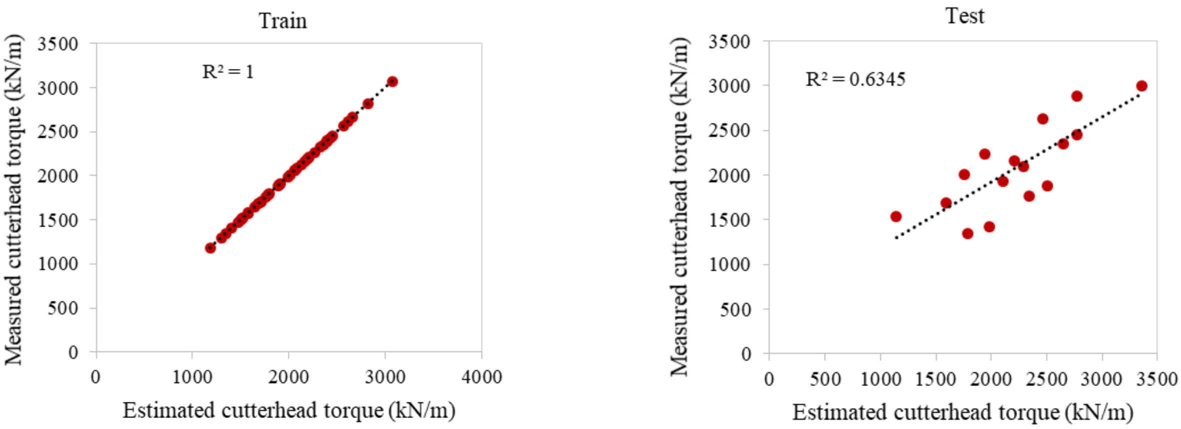

Fig. 10 Comparison of the actual and predicted values of cutterhead torque in training (Left) and experimental (Right) sets using SFL

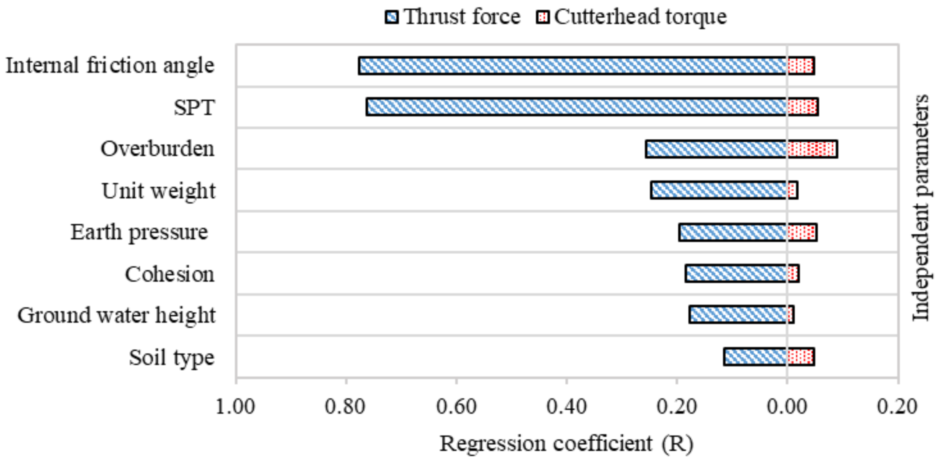

Fig. 11 Diagram of the sensitivity analysis of independent parameters versus thrust force and cutterhead torque using the SFL

constructed based on training and testing data for thrust force and cutterhead torque, respectively. The output of the generated models shows a high $R^2$ between the predicted and observed values. Also, Fig. 11 presents the sensitivity analysis results of the studied parameters.

The RMSE values of the predicted thrust force in the training and testing steps are 7.76e-12 and 1652.5, respectively. However, these values are 82.352 and 1.065e-12 for the cutterhead torque, respectively. According to the sensitivity analysis chart, in SFL models, φ and SPT number of the soil have the highest, while water height from the tunnel invert and soil type show the least effect on the thrust force. Also, tunnel overburden and earth pressure (E) have the greatest effect on the cutterhead torque compared to other parameters.

## 4. Results and discussion

The results of each of the statistical (multivariate linear regression) and artificial intelligence models (ANN and SFL) obtained for TBM parameters (i.e., thrust force and cutterhead torque) and independent parameters influencing the prediction of each model are summarized in Table 10.

Figs. 12 and 13 compare the values obtained from multivariate linear statistical models with the actual values of thrust force and cutterhead torque along the tunnel route, respectively. The results show a 30.9% and 50.7% correlation, respectively, between the predicted values and the actual values of the thrust force and the cutterhead torque along the tunnel route.

Among the artificial intelligence models, SFL models showed the highest correlation coefficient between geotechnical and environmental parameters with machine parameters (thrust force and cutterhead torque). Therefore, it was used as a comparative model with the actual values of boring machine parameters along the tunnel route (Figs. 14 and 15). Overall, this model showed an 89.76 and 85.94% correlation between the predicted and actual values of the thrust force and the cutterhead torque along the tunnel axis, respectively.

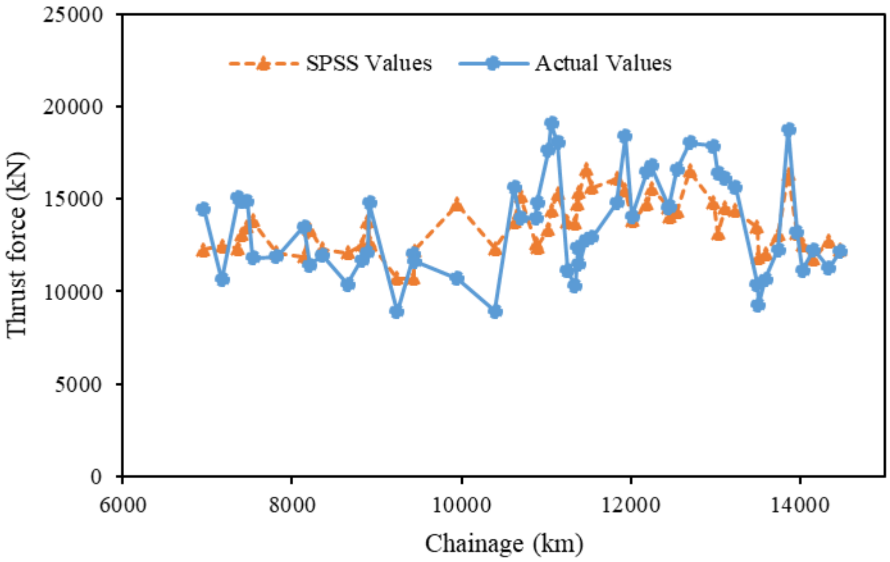

Fig. 12 Comparison of the actual and predicted values of thrust force using multivariate linear regression model along the tunnel alignment

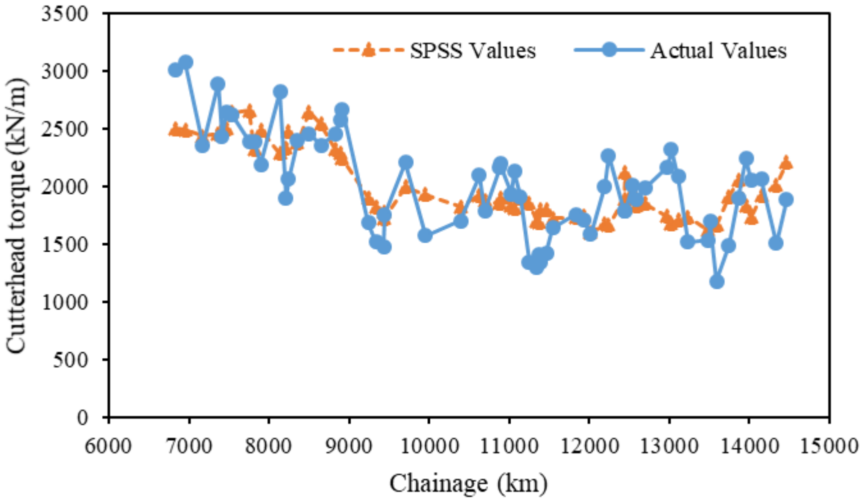

Fig. 13 Comparison of the actual and predicted values of cutterhead torque using multivariate linear regression model along the tunnel alignment

Table 10 Comparison of the results of statistical and artificial intelligence models

| Model | Determination coefficient ($R^2$) | | Effective parameters | |
|---|---|---|---|---|
| | Thrust force | Cutterhead torque | Thrust force | Cutterhead torque |
| Simple Regression | 0.1965 | 0.4795 | Earth pressure | Groundwater height |
| Multivariable Linear Regression | 0.309 | 0.507 | Earth pressure, Groundwater height, Internal friction angle | Soil type, SPT, Groundwater height |
| Artificial Neural Network | 0.1946 | 0.516 | Earth pressure, SPT | All parameters |
| Sugeno Fuzzy Logic (SFL) | 0.728 | 0.6345 | SPT, Internal friction angle | Earth pressure, overburden |

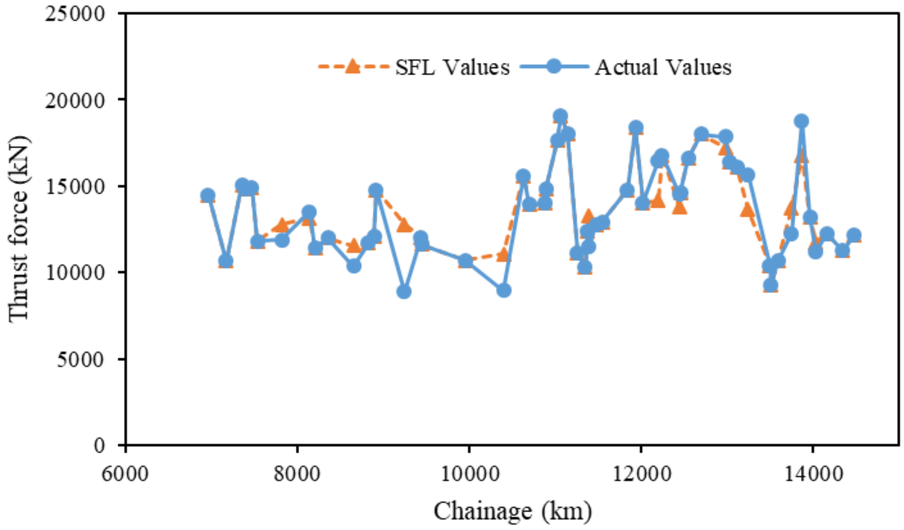

Fig. 14 Comparison of the actual and predicted values of thrust force using the SFL model along the tunnel alignment

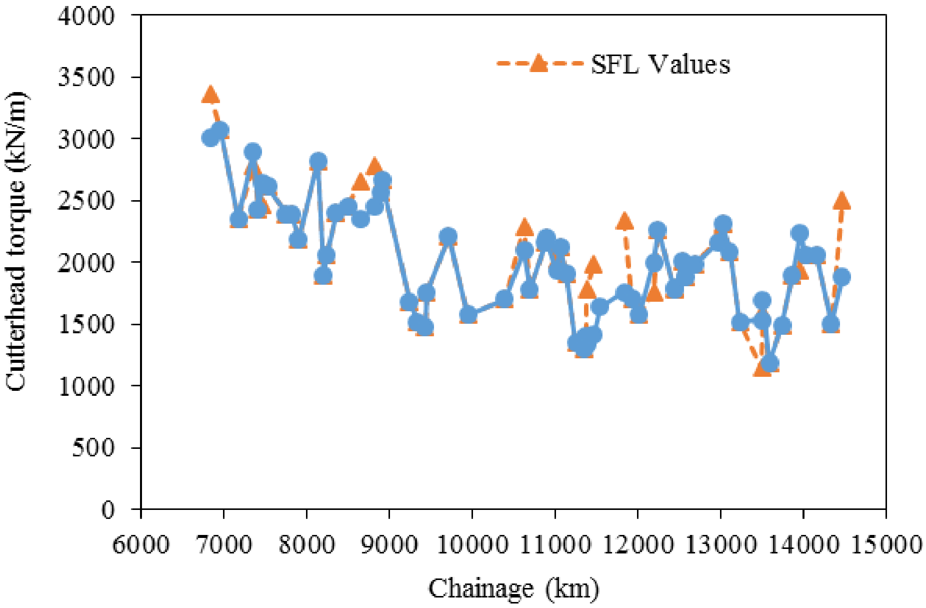

Fig. 15 Comparison of the actual and predicted values of cutterhead torque using the SFL model along the tunnel alignment

## 5. Conclusions

This study investigated the relationship between effective parameters on thrust force and cutterhead torque of an EPB TBM using statistical analysis and artificial intelligence methods to develop a performance-predicting model.

In simple linear regression, the highest coefficient of determination ($R^2$= 0.1965) was achieved between the thrust force and the earth pressure of the confining chamber. In contrast, the simple regression model shows the highest correlation between the cutterhead torque and water height from the tunnel invert ($R^2$= 0.4795). In the multivariate linear regression model, earth pressure, water height from the tunnel invert, and friction showed the greatest effect in estimating the thrust force. The multivariate linear models showed that unit weight and earth pressure have the least effect on the cutterhead torque. On the other hand, standard penetration number, soil type, and water head have the highest impact on cutterhead torque. In estimating the thrust force, the artificial neural network has lower predictions than statistical methods and fuzzy logic models.

The ANN results indicate almost an equal effect of all input parameters in estimating the cutterhead torque. In the Sugeno fuzzy logic model, earth pressure and overburden have the greatest impact on cutterhead torque. Also, friction angle and standard penetration number have the greatest impact on SFL results in predicting the thrust force. The Fuzzy model showed a more than 85% correlation between the actual and estimated values for the whole set of thrust force and cutterhead torque training and testing data.

The variety of cutterhead designs and cutting tools in EPB TBMs (shape, tools arrangement, opening ratio, diameter, etc.) made it complicated to study their performance prediction using conventional methods. Focusing on these subjects is a future plan for extending this paper.

## Acknowledgments

The authors are grateful to the site engineers for their kind cooperation and for providing field data.

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