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ORIGINAL ARTICLE

Prediction of TBM penetration rate from brittleness indexes using multiple regression analysis

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Abstract
One of the most important aspects in the excavation of tunnels with a Tunnel Boring Machine (TBM) is the reliable prediction of its penetration rate. This affects the planning and other decision making on the organization of the construction site of the tunneling project, and, therefore, total costs. In this study, raw data obtained from the experimental works of different researchers were used to establish the new statistical models for prediction of rock TBM penetration rate from brittleness indexes, B_1, B_2, and B_3. For this, correlation between the TBM penetration rate with brittleness indexes statistically was investigated using multiple regression analyses. In these analyses, the TBM penetration rate was considered to be the dependent variable, which is dependent on the independent variables of the brittleness indexes. The validity of the predictive models was validated by statistical tests. The results showed that statistical models are in good accuracy for prediction of TBM penetration rate, and thus making a rapid assessment of the TBM performance.

Keywords TBM · Penetration rate · Brittleness indexes · Statistical models

Introduction

Tunnel Boring Machine (TBM) performance can be measured in terms of the penetration rate. Three main parameters, machine design related parameters, geological conditions and geotechnical properties of rocks along the tunnel alignment affect the TBM penetration rate (Yagiz and Karahan 2015). Although the parameters of drilling machine equipment can be controlled, change to the geological conditions and geotechnical properties of rocks cannot be.

Penetration rate (PR) which is also referred to as Rate of penetration (ROP), and often expressed in m/h and refers to the linear footage of excavation per unit time, when machine engages the ground and is in production (Rostami 2016). Having some prior knowledge of the TBM penetration rate in rock excavation projects is very helpful to plan construction time and to control cost. Penetration rate prediction is considered as a complex and difficult work because of the interaction between rock mass and TBM, but a meaningful task because it is significant for time planning, cost control and choosing the excavation method (Yagiz 2002).

The development of various predictive models of the TBM penetration rate has been main objective and is still under progress for many years (Graham 1976; Hughes 1986; Rostami and Ozdemir 1993; Kahraman et al. 2003; Gong and Zhao 2009; Yagiz and Karahan 2011, 2015; Farrokh et al. 2012; Coffi Adoko et al. 2017). Existing prediction approaches include theoretical and empirical models (Barton 2000; Sapigni et al. 2002), simple and multiple regression analyses (Delisio and Zhao 2014; Farrokh et al. 2012; Khademi Hamidi et al. 2010), artificial intelligence techniques such as artificial neural networks (Benardos and Kaliampakos 2004; Salimi et al. 2016; Shao et al. 2013), fuzzy inference systems (Acaroglu et al. 2008; Alvarez Grima et al. 2000; Yazdani-Chamzini et al. 2013), support vector regression analysis (Mahdevari et al. 2014), particle swarm optimization (Yagiz and Karahan 2011) and other advanced optimization algorithms (Yagiz and Karahan 2015). In general, these models are established on the basis of experience gained and the data compiled from the past tunneling projects in order to derive the complex and non- linear relationship between the TBM penetration rate and the influencing rock mass parameters. Table 1 is a summary of advantages and disadvantages of these modelling concepts.

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Table 1 Advantage/disadvantage of different types of models for performance prediction of rock TBMs (Rostami 2016)

Model type	Advantages	Disadvantages
Theoretical	Flexible with cutter geometry and machine specifications Can be used in tradeoff between thrust and torque and optimization Can be used for cutter head design and improvements Can explain the actual working condition of the discs and related forces	Unable to easily account for rock mass parameters Lack of accounting for joints Can be off by a good margin in jointed rock Inability to account for required field adjustments
Empirical	Proven based on observed field performance of the TBMs in the field Accounts for TBM as the whole system Many of field adjustments (i.e. average cutter conditions) are implied Ability to account for rock joints and rock mass properties	Lower accuracy when used in cases when input parameters are beyond what was in the original field performance database Unable to account for variations in cutter and cutterhead geometry, i.e. cutter tip width, diameter, spacing, gage arrangement Extremely sensitive to rock joint properties

The penetration rate may depend on various rock properties including strength, brittleness, distance between plane of weakness, orientation of discontinuities and also TBM specifications such as torque, thrust, RPM and disc diameter etc. So, the problem is highly complicated to be solved with simple regression approach (Yagiz and Karahan 2015). On the basis of the geological conditions and geotechnical properties of rocks, there are two groups of statistical models for prediction of penetration rate. The first group of models is based on prediction of TBM performance by using a single intact rock parameter. For many researchers, uniaxial compressive and tensile strengths (UCS and BTS) are the most widely used properties for rock drillability (Graham 1976; Farmer and Glossop 1980; Hughes 1986; Karpuz et al. 1990; Akcin et al. 1994; Bilgin et al. 1996; Huang and Wang 1997; Kahraman 1999; Kahraman et al. 2003; Akun and Karpuz 2005; Tanaino 2005). Moreover, many different rock parameters, such as point load index, P-wave velocity, porosity, quartz content, Schmidt hammer number, Shore hardness, cone indenter number, drilling rate index (DRI), coefficient of rock strength (CRS), Cerchar abrasion index (CAI), rock brittleness, texture coefficient (TC), impact strength index (ISI), specific energy (SE), etc. can be used for prediction of TBM performance (McFeat-Smith and Fowel 1977; Howarth 1987; Kovscek et al. 1988; Nilsen and Ozdemir 1993; Akcin et al. 1994; Kahraman 1999; Barton 2000; Kahraman et al. 2003).

However, another group of predictive models attempt to correlate TBM performance to rock mass classifications. Among the most commonly used classification systems, Rock Mass Rating (RMR) and Rock Mass Quality Index (Q) have been used more frequently in TBM performance prediction. These models have been developed based on the historical field data of TBM performance in various ground conditions (Alber 1996; Bruland 1998; Barton 1999; Sapigni et al. 2002; Yagiz 2008; Gong and Zhao 2009; Khademi Hamidi et al. 2010; Benato and Oreste 2015; Yagiz and Karahan 2015; Salimi et al. 2016).

Although in most of the previous studies, different statistical models have been derived for prediction of TBM penetration rate for several decades, the models that are based on the rock brittleness have been limited. Altindag (2000, 2002) found significant correlations between his proposed new brittleness concept (B3) and the penetration rate of percussive drills. Kahraman (2002) statistically studied the relationships between TBM penetration rate and three different brittleness indexes using the raw data obtained from the experimental works of different researchers. It concluded that penetration rate does not exhibit a correlation with the brittleness of B_1 and B_2, but it is strongly correlated with the brittleness of B_3. Influence of rock brittleness on TBM penetration rate in Singapore granite were investigated by Gong and Zhao (2007). These researchers found that TBM penetration rate increases with increasing rock brittleness. Altindag (2010) assessed the relationships between penetration rate with rock brittleness indexes B_1, B_2 and B_3. Results showed that the lower correlation coefficients were found between brittleness B_1 and penetration rate, than brittleness B_2 and B_3.

In this study, by analyzing the raw data sets obtained from the experimental works, multiple regression models are proposed for prediction of TBM penetration rate from brittleness indexes, B_1, B_2 and B_3.

Brittleness

Brittleness is considered as one of the most important properties of rocks, which affect the TBM penetration rate of rocks. Nevertheless, there is no agreement between different authors whether as to definition, or as to measure brittleness. Different researchers mean, express and use it differently (Coates 1966; Hetenyi 1966; Ramsey 1967; Obert and Duvall 1967; Reichmuth 1967; Hucka and Das 1974; McFeat-Smith 1977; Singh 1986; Goktan 1991, 1992; Inyang and Pitt 1990; Inyang 1991; George 1995; Altindag 1997, 2000, 2002; Copur 1999; Kahraman 2002).

Brittleness, in the Glossary of Geology and Related Sciences, is defined as a property of materials that rupture or fracture with little or no plastic flow (AGI 1960). Morley (1944) and Hetenyi (1966) define brittleness as the lack of ductility. Ramsey (1967) defined brittleness as follows: ''When the internal cohesion of rocks is broken, the rocks are said to be brittle''. Obert and Duvall (1967) defined brittleness as follows: ''materials such as cast iron and many rocks usually terminate by fracture at or only slightly beyond the yield stress''. Hucka and Das (1974) stated that with higher brittleness the following facts can be observed:

- Low values of elongation
- Fracture failure
- Formation of fines
- Higher ratio of compressive to tensile strength
- Higher resilience
- Higher angle of internal friction
- Formation of cracks in indentation

George (1995) defined that rock brittleness is the ability of a rock material to deform continuously and perpetually without apparent permanent deformations along with the application of stress surpassing the necessary stresses for microcracking of the material.

Direct standard testing method for determination of rock brittleness have not available yet. Therefore, rock brittleness is indirectly obtained as a function of rock strength. Uniaxial compressive and Brazilian tensile strengths are simply defined and easily obtained; they are often used in determining the brittleness (Altindag 2002; Kahraman 2002). In this study, three most common approaches are used for measuring brittleness value.

$$B_1 = \sigma_c / \sigma_t \tag{1}$$

$$B_2 = (\sigma_c \times \sigma_t)/2,\ \mathrm{MPa}^2 \tag{2}$$

$$B_3 = \sqrt{B_2},\ \mathrm{MPa} \tag{3}$$

where, B_1, B_2 and B_3 are brittleness indexes, σ_c is the uniaxial compressive strength (MPa) and σ_t is the Brazilian tensile strength (MPa).

Brittleness indexes, B_1, B_2 and B_3 are widely used in the literature such as Beron et al., (1983), Chiu and Johnston (1983), Kim and Lade (1984), Vardoulakis (1984), Koulikov (1987), Inyang and Pitt (1990), Goktan (1991), Inyang (1991), Kahraman (2002), and Atici and Ersoy (2009).

Materials and methods

Three separate data sets were compiled from the review of experimental works of different researchers. (Selim and Bruce 1970; Bilgin et al. 1993; Kahraman 1999). Uniaxial compressive strength, Brazilian tensile strength and penetration rate data obtained from the different researchers, and calculated brittleness indexes values (B_1, B_2, and B_3) by the author were listed in Tables 2, 3 and 4. The relationships between the TBM penetration rate values and brittleness indexes were investigated by simple and multiple regression models and most suitable regression model for estimating the penetration rate from the brittleness indexes were proposed. The methodology of the research is given in Fig. 1.

The distribution of the three different rock classes for all studied rocks is given in Fig. 2. The rock classes that was included in this study are 22 sedimentary, 5 igneous and 1 metamorphic.

Studied rocks are classified according to their UCS values as suggested in ISRM (2007) (Fig. 3). This Figure shows that rocks were classified as having a weak strength (5–25 MPa), low strength (25–50 MPa), medium strength (50–100 MPa), high strength (100–250 MPa) and very high strength (> 250 MPa).

According to the classification of rocks based on the brittleness of B_1 by Aftes (2003) (Table 5), most of the rocks are classified as rocks with middle brittle (B1: 10–15), and the other rocks fall into the classes with low brittle ($B_1 < 10$) and brittle (B_1: 15–25).

Results and discussion

Traditionally, statistical methods such as simple and multiple regression techniques are used to found prediction models. In addition to these conventional methods, new techniques have garnered considerable attention. These techniques are based on genetic algorithm, support vector regression,

Table 2 The field test data of percussion drilling (Selim and Bruce 1970) and calculated brittleness values

Rock type	Rock class	PR (cm/min)	σ_c (MPa)	σ_t (MPa)	Brittleness indexes[a]		
					B_1	B_2	B_3
Mankato stone	Sedimentary	82.6	54.1	9.5	5.69	257.0	16.03
Kasota stone	Sedimentary	90.4	103.7	6.4	16.20	331.8	18.22
Rockville granite	Igneous	52.2	144.1	10.8	13.34	778.1	27.90
Rainbow granite	Igneous	44.9	198.2	14.3	13.86	1417.1	37.64
Charcoal granite	Igneous	41.0	234.2	12.4	18.89	1452.0	38.11
Dresser basalt	Igneous	20.6	312.8	17.5	17.87	2737.0	52.32
Jasper quartzite	Metamorphic	40.0	396.5	18.7	21.20	3707.3	60.89
Aurora Taconite A	Sedimentary	37.1	451.3	31.1	14.51	7017.7	83.77
Babbitt Taconite B	Sedimentary	25.6	473.5	21.4	22.13	5066.5	71.18

Drilling conditions: Operating pressure: 632.7 kPa, Feed pressure: 492 kPa

[a]Calculated by the author

Table 3 The field test data of rotary drills (Bilgin et al. 1993) and calculated brittleness values

Rock type	Rock class	PR (cm/min)	σ_c (MPa)	σ_t (MPa)	Brittleness indexes[a]		
					B_1	B_2	B_3
Marl	Sedimentary	78	88.7	6.0	14.78	266.1	16.31
Limestone	Sedimentary	97	77.5	5.5	14.09	213.1	14.60
Marl	Sedimentary	61	82.4	6.3	13.08	259.6	16.11
Marl	Sedimentary	63	69.2	5.0	13.84	173.0	13.15
Marl	Sedimentary	147	66.6	6.5	10.25	216.5	14.71
Marl	Sedimentary	133	16.1	1.4	11.50	11.3	3.36
Marl	Sedimentary	203	46.9	4.5	10.42	105.5	10.27
Marl	Sedimentary	185	45.5	5.3	8.58	120.6	10.98
Tuff	Igneous	198	43.4	4.0	10.85	86.8	9.32
Mar–Limestone	Sedimentary	152	61.5	5.7	10.79	175.3	13.24
Marl	Sedimentary	268	7.9	0.8	9.88	3.2	1.78
Marl	Sedimentary	243	10.6	1.0	10.60	5.3	2.30

Drilling conditions: Hole diameter: 258 mm, Bit type: WC, Thrust: 4644–5031 kg, Rotation: 119 rpm

[a]Calculated by the author

Table 4 The field test data of DTH drills (Kahraman 1999) and calculated brittleness values

Rock type	Rock class	PR (cm/min)	σ_c (MPa)	σ_t (MPa)	Brittleness indexes[a]		
					B_1	B_2	B_3
Limestone	Sedimentary	35	15.7	0.9	17.44	7.1	2.66
Limestone	Sedimentary	14	85.2	9.1	9.36	387.7	19.69
Dolomite	Sedimentary	28	96.3	10.7	9.00	515.2	22.70
Limestone	Sedimentary	20	49.9	4.1	12.17	102.3	10.11
Limestone	Sedimentary	12	76.1	7.5	10.15	285.4	16.89
Gravelled limestone	Sedimentary	23	36.2	2.7	13.41	48.9	6.99
Limestone	Sedimentary	18	68.4	7.5	9.12	256.5	16.02

Drilling conditions: Bit diameter: 90–100 mm, Operating pressure: 6–8 bar, Air pressure: 5–8 bar, Pull-down pressure: 13–80 bar

[a]Calculated by the author

probabilistic and soft computing techniques, such as artificial neural networks, regression trees, adaptive neuro-fuzzy inference systems, fuzzy inference systems, a hybrid ANN and GA, hybrid ANN and imperialist competitive algorithm, and hybrid ANN and particle swarm optimization technique

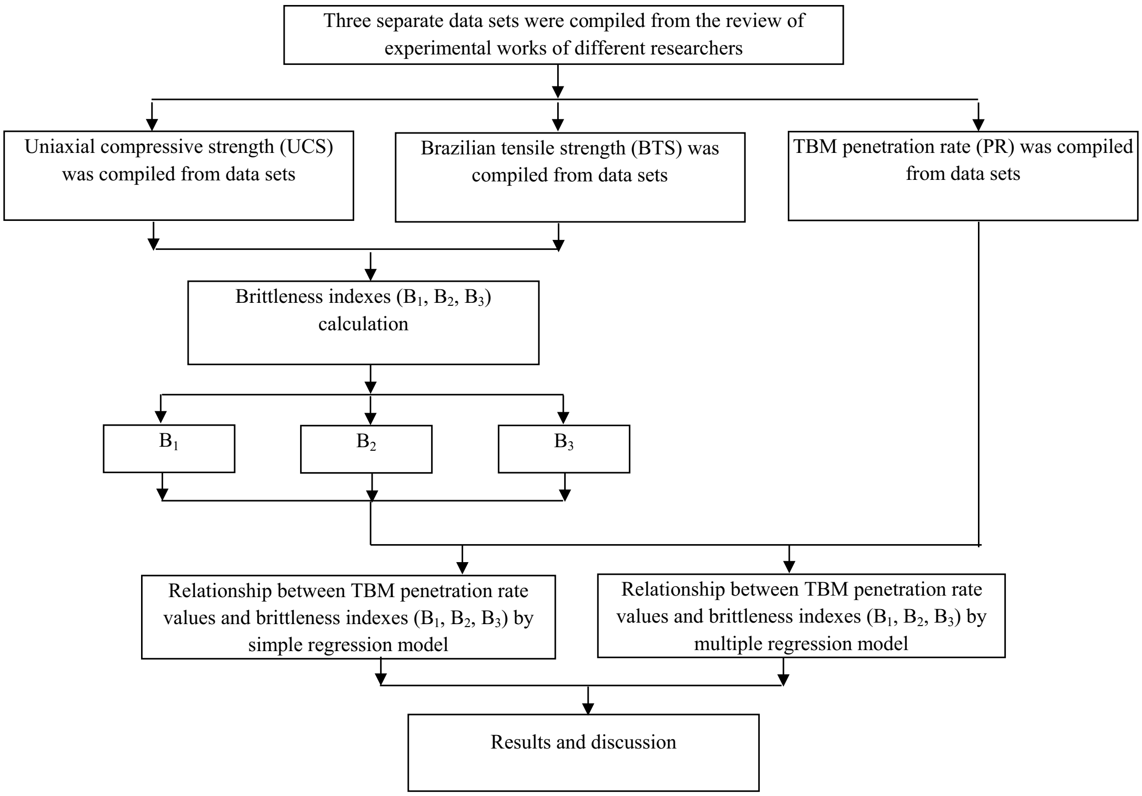

Fig. 1 Methodology of the research

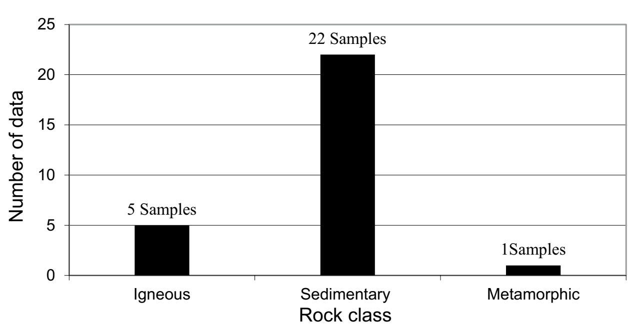

Fig. 2 Distribution of the three different rock classes for all data sets

(Barzegar et al. 2016; Barzegar and Moghaddam 2016; Heddam 2016a, b; Keshavarzi et al. 2016).

Simple regression is the simplest form of regression analysis involving one independent variable and one dependent variable. In this regression, the dependent variable is approximated by an independent variable. Multiple regression analysis is an approach for modeling the relationship between a dependent variable and two or more independent variables. This technique is more amenable to ceteris paribus analysis because it allows researchers to explicitly control many other factors (independent variables) that simultaneously affect the dependent variable. In this study, simple and multiple regression models were performed for estimating the TBM penetration rate from the brittleness indexes.

Model based on simple regression analysis

In this section, simple regression analysis is carried out to find relationships between TBM penetration rate and brittleness indexes of studied rocks. For this purpose, data given in Tables 1, 2 and 3 were analyzed using the least square regression method.

The author this work attempted to develop the best correlation, linear ($y = ax + b$), power ($y = ax^b$), exponential ($y = ae^x$) or logarithmic ($y = a + \ln x$), between penetration rate with brittleness indexes B_1, B_2 and B_3 to attain the most reliable empirical model. The model of the best fit line, the 95% confidence limits and the determination coefficients (R^2) were determined for each correlation. The results of simple regression analysis and the determination coefficients are summarized in Table 6 and graphically illustrated in Figs. 4, 5 and 6. It can be seen from this Table that low correlations were found between penetration rate with brittleness indexes for all data sets in this study (R^2 ranging from 0.40 to 0.78). However, there are better correlations between penetration rate with B_2 ($R^2 = 0.78$) and B_1 ($R^2 = 0.71$) in

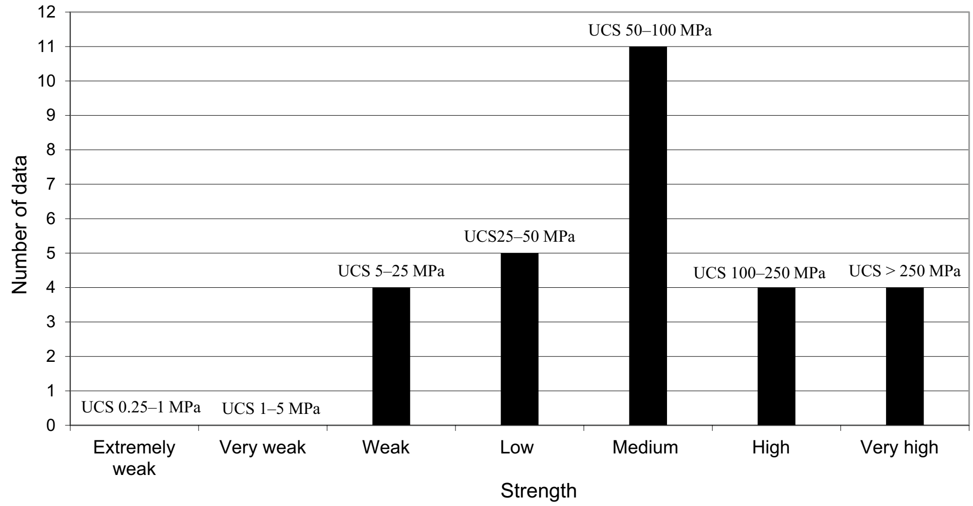

Fig. 3 Uniaxial compressive strength classification of studied rocks belonging to all data sets (ISRM 2007)

Table 5 Description of rock brittleness (Aftes 2003)

Class	B_1 value	Description
1	> 25	Very brittle
2	15–25	Brittle
3	10–15	Middle brittle
4	< 10	Low brittle

data sets of Selim and Bruce (1970) and Bilgin et al., (1993), respectively.

According to the statistical models derived from this study (Table 5), penetration rate decreases with increasing brittleness indexes B_1, B_2 and B_3 for all data sets, except regression model between penetration rate and brittleness index B_1 in Kahraman (1999) research.

The derived statistical models in this study were compared with those available in the literature. The results of this study are in accordance with the findings of Kahraman (2002) and Altindag (2010). Kahraman (2002) obtained an exponential relationship with high correlation coefficient between the penetration rate of rotary drills and the brittleness of B_1. Altindag (2010) investigated the relationships between penetration rate with rock brittleness indexes B_1, B_2 and B_3. Results of this researcher showed that penetration rate decreases with increasing brittleness indexes. However, there is a significant difference between the results of this study, Kahraman (2002) and Altindag (2010) with Gong and Zhao (2007) results. Gong and Zhao (2007) evaluated the effect of rock brittleness on TBM penetration rate in Singapore granite. Their results show that penetration rate increases with increasing brittleness index B_1.

Model based on multiple regression analysis

Multiple regression analysis was performed to determine the relationships between penetration rate and brittleness indexes. In these analyses, the dependent variable is the penetration rate and the independent variables are brittleness indexes B_1, B_2 and B_3. In this study, the general model for prediction of penetration rate is as follows:

Table 6 Results of simple regression analysis between penetration rate and brittleness indexes

References	Equation code no.	Regression model	Determination coefficients (R^2)
Selim and Bruce (1970)	S_1	$\mathbf{PR} = 115.63e^{-0.061\mathbf{B1}}$	0.40
	S_2	$\mathbf{PR} = -17.97 \ln(\mathbf{B_2}) + 180.17$	0.78
	S_3	$\mathbf{PR} = -35.94 \ln(\mathbf{B_3}) + 180.17$	0.78
Bilgin et al., (1993)	S_4	$\mathbf{PR} = 1792.3e^{-0.223\mathbf{B1}}$	0.71
	S_5	$\mathbf{PR} = -0.5727\,\mathbf{B_2} + 230.42$	0.63
	S_6	$\mathbf{PR} = -9.975\,\mathbf{B_3} + 257.18$	0.59
Kahraman (1999)	S_7	$\mathbf{PR} = 1.7854\,\mathbf{B_1} + 0.8574$	0.47
	S_8	$\mathbf{PR} = -3.626 \ln(\mathbf{B_2}) + 38.976$	0.46
	S_9	$\mathbf{PR} = -7.251 \ln(\mathbf{B_3}) + 38.976$	0.46

TBM penetration rate: PR, Brittleness indexes: B_1, B_2 and B_3

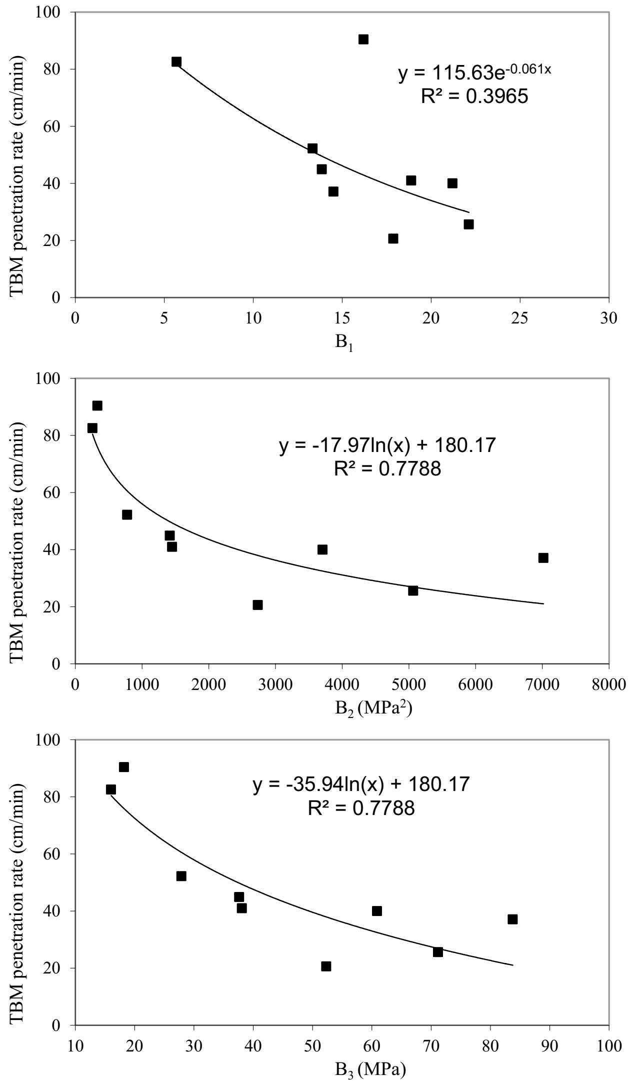

Fig. 4 Relationship between TBM penetration rate with **a** B_1, **b** B_2, **c** B_3 (from Table 2)

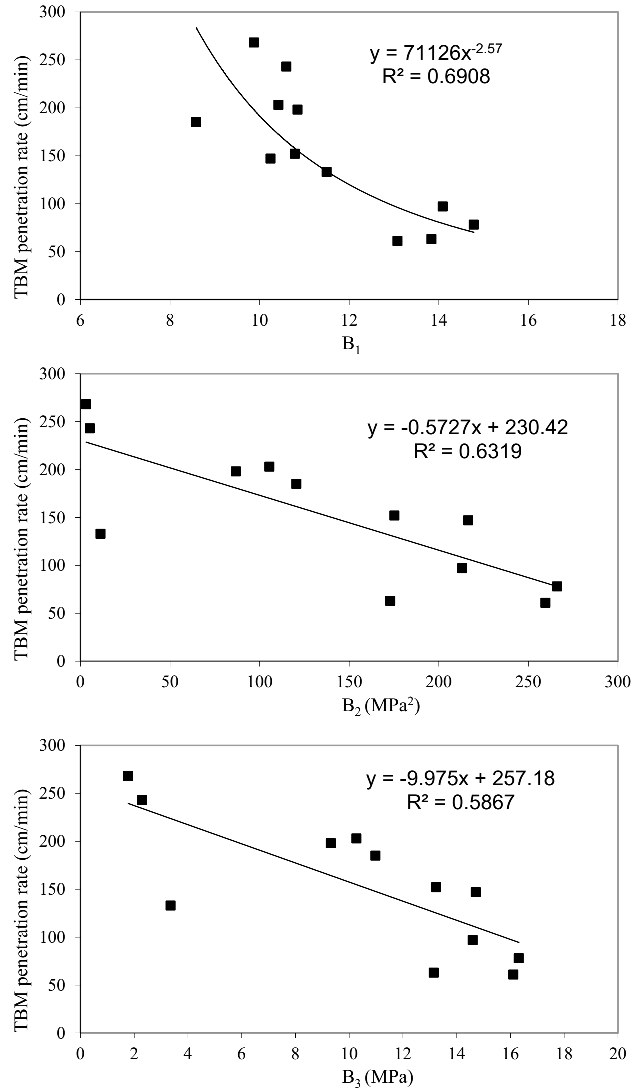

Fig. 5 Relationship between TBM penetration rate with **a** B_1, **b** B_2, **c** B_3 (from Table 3)

$$PR = \alpha_0 + \alpha_1 B_1 + \alpha_2 B_2 + \alpha_3 B_3 \tag{4}$$

where PR is the predicted value of the TBM penetration rate, B_1, B_2 and B_3 are the brittleness indexes, α_0 is a constant, and α_1, α_2 and α_3 are the regression coefficients of B_1, B_2 and B_3, respectively.

The data given in Tables 2, 3 and 4 were analyzed using SPSS®.v.21 statistical software. The results of these analyses are summarized in Table 6. Determination coefficient, standard error of estimate, F statistics test and the plots of actual values vs. predicted values were used for the evaluation of the produced models from the multiple regression analyses.

The degree of fit to a curve can be measured by the value of the determination coefficient (R^2), which measures the proportion of variation in the dependent variable, and the standard error of estimate (SEE), which is an important measure for indicating how close the actual data points fall to the predicted values on the regression curve. The R^2 and SEE values for multiple regression models are given in Table 6. The R^2 values of models M1, M2 and M3 given in Table 7 is higher than 0.81 that are at acceptable level. This shows that the proposed models fit the data well and are capable for prediction of penetration rate. The SEE value for models M1, M2 and M3 is 7.96, 34.99 and 3.47, respectively. These measures show that the models given in Table 7 can be accepted as a reliable predictor for the penetration rate.

The variance analysis technique is used for testing significance of regression in multiple regressions. For this purpose, the F statistics test was performed for testing the global usefulness of the models. This test is widely used

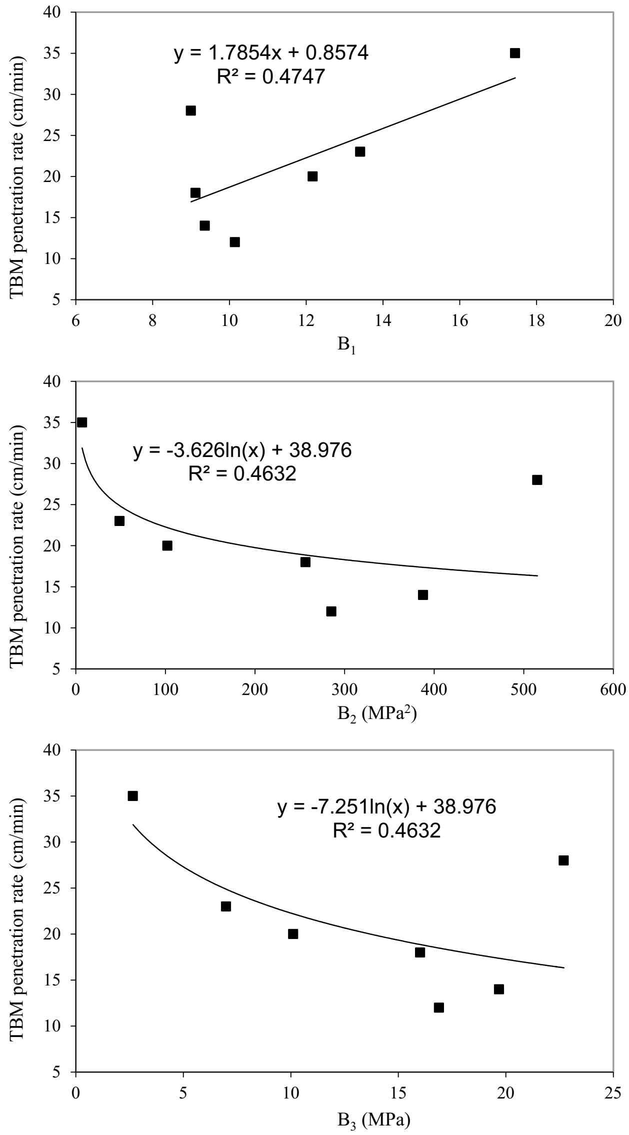

Fig. 6 Relationship between TBM penetration rate with **a** B_1, **b** B_2, **c** B_3 (from Table 4)

in regression and analysis of variance. The computations for F statistics test are shown in Table 7. For all models, significance F–value within the 95% confidence interval is lower than 0.05. If the F–ratio is greater than the F-tabulated value obtained from the F distribution table, then it can be said that the regression is significant (Stoodley and Lewis 1980). Since all the computed F–ratios of the models are greater than the F-tabulated value, it could be concluded that those are significant and so are appropriate for prediction of penetration rate.

Although, the determination coefficients (R^2) of the models are between 0.81 and 0.95 and this is good value, it is not identifies the valid models necessarily. Therefore, for validating the models M1, M2 and M3, the actual values were plotted against the predicted values. A summary of the results of the actual and predicted penetration rate values are given in Tables 8, 9 and 10 and graphically in Figs. 7, 8 and 9. The error in the predicted value is represented by the distance that each data point has from the 1:1 diagonal line. A point lying on the line indicates an exact prediction. The figures indicate that the data points fall close to the 1:1 slope line and are scattered uniformly around it, suggesting that models appropriate for prediction of TBM penetration rate using brittleness indexes. On the other hand, it is seen in Figs. 7, 8 and 9 that a significant concurrence is identified between actual and predicted penetration rate values, with a high determination coefficients (R^2) between 0.81 and 0.93, indicating strong relationships.

The results of multiple regression analysis (Table 7) were compared with simple regression analysis (Table 6) based on their determination coefficients. It is worth to noting that there is a significant difference between the determination coefficients these analyses. The determination coefficients derived using multiple regression models were generally higher than those obtained using simple regression models. For instance, in Selim and Bruce (1970) research, the determination coefficient value based on multiple regression models is 0.93 (Table 7, Eq. M1); whereas those obtained by simple regression models are 0.40 to 0.78 (Table 6, Eq. S1, S2 and S3). Therefore, models based on multiple regression

Table 7 Summarized the multiple regression analysis results

Equation code no.	References	Regression equations	Determination coefficient (R^2)	Standard error of estimate (SEE)	Tabulated F-ratio	F-ratio	Significance F
M1	Selim and Bruce (1970)	$\mathbf{PR}=135.24+1.219\ \mathbf{B_1}+0.035\ \mathbf{B_2}-4.322\ \mathbf{B_3}$	0.93	7.96	5.41	21.0	0.003
M2	Bilgin et al. (1993)	$\mathbf{PR}=460.74-20.67\ \mathbf{B_1}+0.116\ \mathbf{B_2}-8.125\ \mathbf{B_3}$	0.81	34.99	4.07	11.7	0.003
M3	Kahraman (1999)	$\mathbf{PR}=140.73-4.757\ \mathbf{B_1}+0.269\ \mathbf{B_2}-9.288\ \mathbf{B_3}$	0.91	3.47	9.28	9.7	0.047

TBM penetration rate: PR, Brittleness indexes: B_1, B_2 and B_3

Table 8 The actual values of penetration rate from Selim and Bruce (1970) research (Table 2) and their predicted values from Eq. (M1) developed given in this study

Rock type	Actual penetration rate (cm/min)	Predicted penetration rate (cm/min)
Mankato stone	82.6	81.9
Kasota stone	90.4	87.9
Rockville granite	52.2	58.2
Rainbow granite	44.9	39.0
Charcoal granite	41.0	44.4
Dresser basalt	20.6	26.7
Jasper quartzite	40.0	27.7
Aurora Taconite A	37.1	36.5
Babbitt Taconite B	25.6	31.9

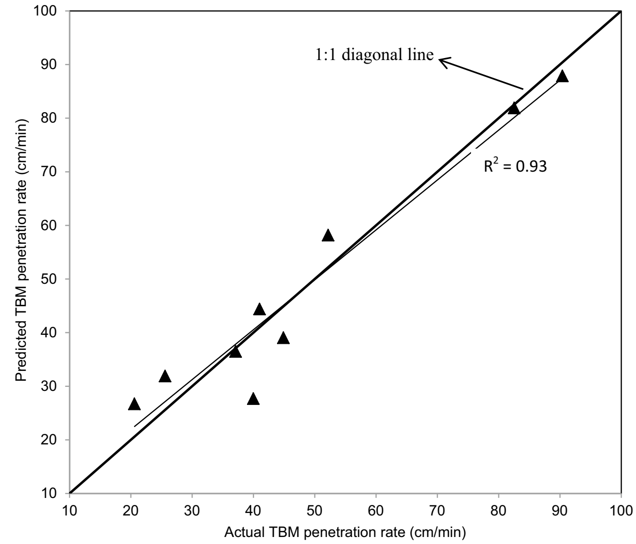

Fig. 7 The actual values of penetration rate from Selim and Bruce (1970) research and their predicted values from Eq. (M1) developed in this study

Table 9 The actual values of penetration rate from Bilgin et al. (1993) research (Table 3) and their predicted values from Eq. (M2) developed given in this study

Rock type	Actual penetration rate (cm/min)	Predicted penetration rate (cm/min)
Marl	78	53
Limestone	97	76
Marl	61	90
Marl	63	88
Marl	147	155
Marl	133	197
Marl	203	174
Marl	185	208
Tuff	198	171
Marl–Limestone	152	150
Marl	268	243
Marl	243	224

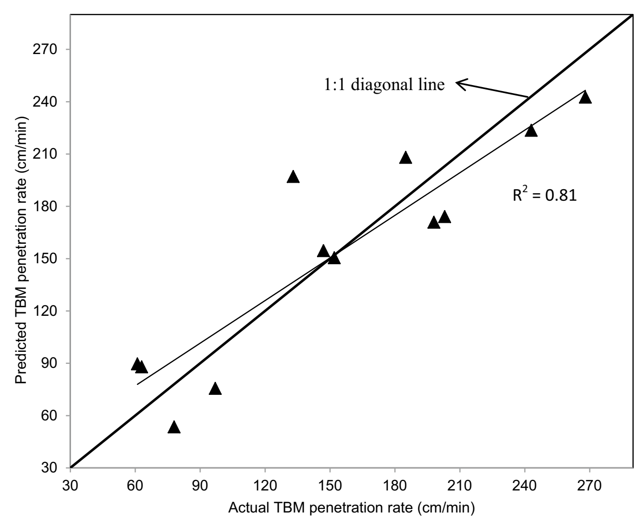

Fig. 8 The actual values of penetration rate from Bilgin et al. (1993) research and their predicted values from Eq. (M2) developed in this study

Table 10 The actual values of penetration rate from Kahraman (1999) research (Table 4) and their predicted values from Eq. (M3) developed given in this study

Rock type	Actual penetration rate (cm/min)	Predicted penetration rate (cm/min)
Limestone	35	35
Limestone	14	18
Dolomite	28	26
Limestone	20	16
Limestone	12	12
Gravelled limestone	23	25
Limestone	18	18

analysis are more reliable than those obtained by simple regression analysis for prediction of penetration rate.

Conclusions

In this study, simple and multiple regression analyses were performed for prediction of TBM penetration rate from brittleness indexes B_1, B_2 and B_3. For this, the raw data sets obtained from the experimental works were used. Based on statistical analyses, simple and multiple regression models were developed and their significant was assessed by determination coefficient (R^2), standard error of estimate (SEE),

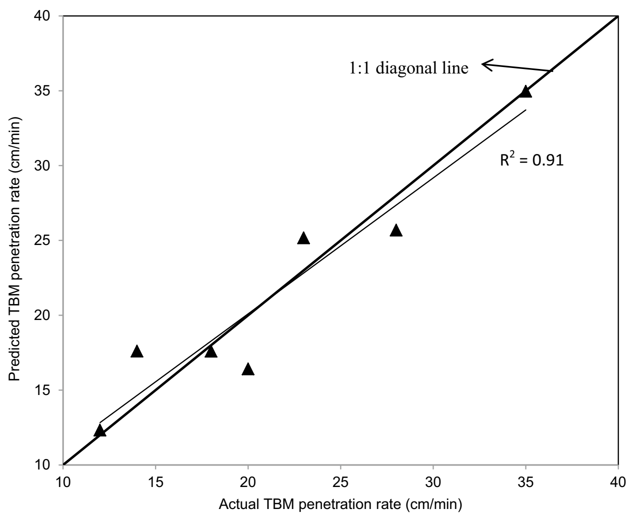

Fig. 9 The actual values of penetration rate from Kahraman (1999) research and their predicted values from Eq. (M3) developed in this study

F statistics test and the plots of actual values vs. predicted values.

Using data analysis higher determination coefficient values (R^2) were obtained for the multiple regression models (ranging of 0.81–0.93) as compared with those that obtained for the simple regression models (ranging of 0.40–0.78). This shows that multiple regression models are the more appropriate and reliable than simple regression models for prediction of penetration rate using the brittleness indexes.

The practical application of the proposed multiple regression models is that simple brittleness indexes B_1, B_2 and B_3, which determined based on compressive and tensile strengths, can be used for prediction of penetration rate. Consequently, the multiple regression models developed in this study provides significant practical advantages for decision making on the organization of the construction site of the tunneling project, and, therefore, total costs.

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