Rock cutting force estimation in tunneling with TBM

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ORIGINALITY STATEMENT

I, Olzhas Arinov, hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, or substantial proportions of material which have been accepted for the award of any other degree or diploma at Nazarbayev University or any other educational institution, except where due acknowledgement is made in the thesis.

Any contribution made to the research by others, with whom I have worked at NU or elsewhere is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except to the extent that assistance from others in the project's design and conception or in style, presentation and linguistic expression is acknowledged.

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ABSTRACT

The performance of TBM affects the execution cost and completion time of the rock excavation project. Therefore, it is vital to correctly predict the performance of TBM. Despite the large amount of research about TBM performance and estimation of its parameters, there is still a gap. Predicting cutting force remains a complex task due to the variability in rock conditions and properties, the diversity of TBM types, and the need to consider all relevant parameters and properties together. Therefore, it is necessary to analyze data using regression models based on statistical analysis. This thesis aims to address the performance prediction problem and improve the performance prediction model by gaining a better understanding of the interaction between rock and cutting force. To achieve the goal of this study, simple linear, multilinear and non-linear regression analysis based on statistical analysis approaches were employed to develop a series of TBM performance model. A comprehensive database of TBM performance compiled from 3 tunnelling projects of Iran (Zagros, Ghomrood and Karaj), was established and used for the development of the model. The results of the study showed the influence of different rock parameters on the cutting force. Also, the quality of the rock has a significant impact on the cutting force. The results indicated that non-linear equations are more robust than linear models because linear relationships are less realistic under such volatile and unpredictable conditions. Compared to previous research, the current model, which utilizes intact rock properties and rock mass properties, has demonstrated favorable outcomes. This implies that the equations are dependable in predicting TBM (Tunnel Boring Machine) performance and can be utilized in situations where machine parameters are lacking. The conclusion drawn was that intact rock properties serve as the primary input parameters for predicting TBM performance. However, relying solely on intact rock properties may be insufficient, as in cases of fragmented rock, they may not adequately reflect the strength of the rock mass. It is also important to note that using the prediction formula without machine parameters can lead to inaccurate results, since machine parameters are also volatile in different conditions and affect the performance of TBM in a complex way. Method can be used for more extensive analysis, but limitations such as unrealistic values when imputing data must be taken into account.

Key words: Tunnel Boring Machine (TBM), TBM performance, cutting force estimation, rock properties, empirical equations.

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1. INTRODUCTION

1.1 Background/Problem Definition

According to Paltrinieri (2015), mechanized tunneling is now increasingly seen as a valid alternative to drilling and blasting. In the tunnel industry, compared with traditional technology, tunnel boring machines (TBMs) are better because the rate of penetration is higher, the working conditions are safer, less damage to the surface and continuous operation. Although TBM performance is high and existence of significant fault zones is determined at the design stage, sometimes TBM performance can be reduced due to unexpected ground conditions or due to underestimation of fault zones or other problems (Barla and Pelizza, 2000). During the construction and planning stages, it is important to have a better understanding of the occurrence of weak zones in the tunnel and the geological development of the tunnel, since these types of problems usually only occur in 1-15% of the tunnel (Palmström and Bertelsen, 1988). It is necessary to take into account the complexity of the ground conditions when laying the tunnel in order to avoid increasing the cost of the project, and this also affects the safe operation (Paltrinieri, 2015). The machine parameters are also have influence to prediction of the penetration rate which effects on cost and planning. Therefore, this project develops a model based on statistical analysis which shows the correlation between rock properties and machine parameters, especially cutting forces.

1.2 Problem Statement

Rock cutting force estimation is a critical aspect in the field of tunneling with Tunnel Boring Machines (TBMs), as it directly affects the efficiency and effectiveness of the tunneling process. Accurate estimation of rock cutting force can help optimize the TBM operation, reduce wear and tear on the machine, and enhance the overall productivity of the tunneling project. Traditional methods of estimating rock cutting force in tunneling rely on empirical models that may not always accurately capture the complex and dynamic nature of rock cutting behavior (Fukui and Okubo, 2006).

According to Yagiz et al. (2021) the variability and heterogeneity of rock properties, such as strength, abrasivity, and brittleness, pose challenges in developing accurate regression models. The relationships between these rock properties and cutting force may not be well understood, and the lack of a comprehensive database of rock properties can further hinder the accuracy of the predictive models. Accurate estimation of rock cutting force remains a challenging task due to the complex and variable nature of rock properties, as well as the limitations of traditional analytical approaches.

Therefore, the main problem addressed in this thesis is the accurate estimation of rock cutting force in tunneling with TBMs using regression analysis based on statistical analysis, taking into consideration the challenges posed by the variability of rock properties, the complex interaction between operational parameters and rock properties, and the dynamic nature of rock cutting behavior during tunneling.

1.3 Project Objectives

The objective of this thesis is to estimate the relationship between cutting force and rock properties using empirical models. To achieve this objective, the following specific goals have been identified:

- Conduct a literature review to evaluate excavation methods, TBM machine parameters, and qualities of intact rock in order to gain a critical understanding of the current state of knowledge in the field.
- Collect raw database information from literature sources on TBM tunnel excavations in Iranian tunnel projects to support the development of a cutting force estimation model.
- Develop and evaluate both linear and non-linear models for calculating rock cutting force, and use these models to determine the impact of input parameters on cutting force for Iranian tunnel projects.

The thesis is organized into five sections. The first two sections provide an introduction and literature review, respectively. The following two sections focus on proposing new equations for assessing rock cutting force. The final section consist of a reference list.

1.4 Project significance to the industry

As the use of tunnel tunneling machines is increasingly used in various industries such as mining, there is an increasing need to properly assess the performance of the machine. The results obtained in this thesis can be used to predict the performance of TBM more accurately, which in turn affects more efficient production planning and the economic component of such projects.

2. LITERATURE REVIEW

2.1 INTRODUCTION

In 20th century there were several attempts to simulate a model for evaluating the effectiveness of TBM on difficult ground conditions. These attempts, which have neither a specific comprehensive formulation nor a conclusion, can be divided into empirical and theoretical models (Samaei et al., 2020). Studies based primarily on laboratory tests that examine the effect of the cutter disk on rock sample, TBM performance and other related issues are defined as theoretical. But theoretical models were gradually not developed due to the lack of necessary equipment in laboratories and the difficulty of ensuring the conditions of field rocks in the laboratory (Rostami and Ozdemir, 1997). Empirical studies are carried out both on the basis of field data on the properties of the rock mass, and on the parameters recorded by the machine (Zareh Nagadekhi and Ramezanzadeh, 2017). Rock mass properties include rock mass rating (RMR), drilling rate index (DRI), rock quality designation (RQD), quartz content, the distance between planes of weaknesses (DPW), angle between planes of weakness and TBM driven direction (α), the Brazilian tensile strength (BTS), the uniaxial compressive strength (UCS), the brittleness index (BI), the joint spacing (JS), and etc. While machine parameters are power, torque, thrust force, rolling force, cutter load, number of cutters, and etc. Farrokh et al. (2012) assume that these methods can be divided into four groups: computer aided models, simple models, probabilistic models and multiple parameters models.

Based on the cutting force of the machine, it is necessary to develop a new estimation model based on statistical analysis. Because statistical analysis techniques, such as regression analysis, have gained increasing attention for their potential to improve the accuracy of rock cutting force estimation in tunneling. These techniques leverage the availability of large datasets of rock properties, TBM operational parameters, and cutting performance data to train predictive models.

2.2 TUNNEL BORING MACHINES

The type of Tunnel Boring Machine is important for its performance, as each type of TBM has its own feature and scope. Three types of TBM will be discussed below: Open TBM, Single shield TBM and Double shield TBM. TBM Disc Cutters are also important part of tunnel boring machine which has influence to its performance. The main TBM parameters will be considered in the following section.

2.2.1 Open TBM

Open Tunnel Boring Machine (Gripper) could be used for hard rock, and it can be use without heavy supports. In this case, the performance of the machine will not change significantly under the influence of rock fractures. According to Sapigni et al. (2002) machine utilization increases as the rate of penetration decreases if the rock mass is massive. Figure 1 illustrates the simple Open TBM.

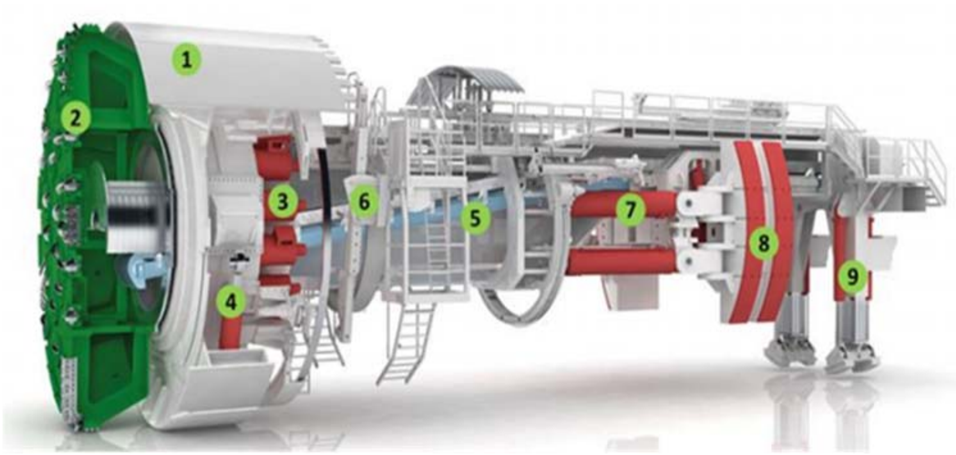


Figure 1. Construction of Open TMB (Brabant and Duhme, 2017)

Open TBMs are more popular than other types of machines in tunnel projects. Brabant and Duhme (2017) state that the fastest and most useful type of machine is the open TBM for use in stable rock formations.

2.2.2 Single shield TBM

In rock mass with a medium frequency of fracturing, Single Shield TBM could be used. Since in such conditions the shield helps to support the machine itself and protect it from damage. The parts of Single shield TBM is shown in Figure 2.

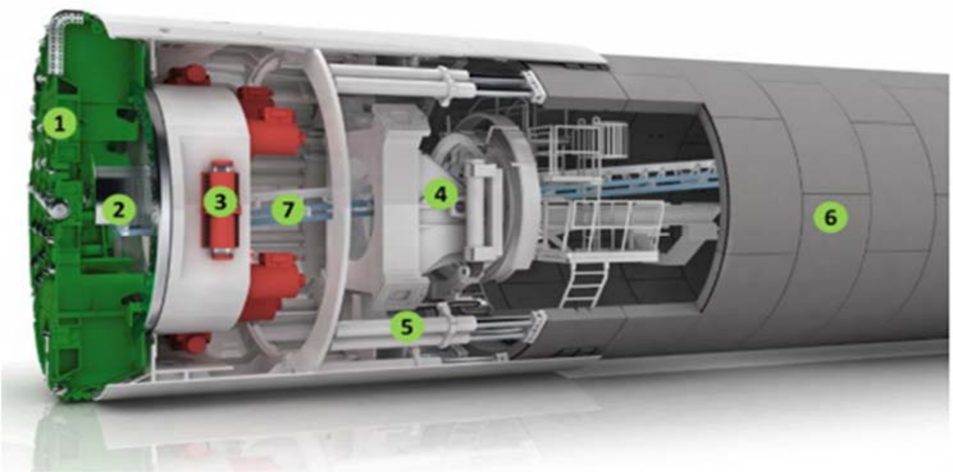


Figure 2. Single shield TBM (1- cutterhead; 2- muck ring; 3- hydraulic torque box; 4- erector; 5- thrust cylinders; 6- segmental lining; 7- belt conveyor) (Brabant and Duhme, 2017)

Mostly the Single shield TBM is used in rock with low strength. Single TBM is comparatively safer than other types in fractured rocks.

2.2.3 Double shield TBM

Double shield TBM is the safest and most productive way to tunnel. In rocks with very strong fracturing, in weak or defective zones, this type of machine is used. A double shield TBM is used for maximum performance, which is the main mechanism of the machine. Figure 3 shows a double shield TBM.

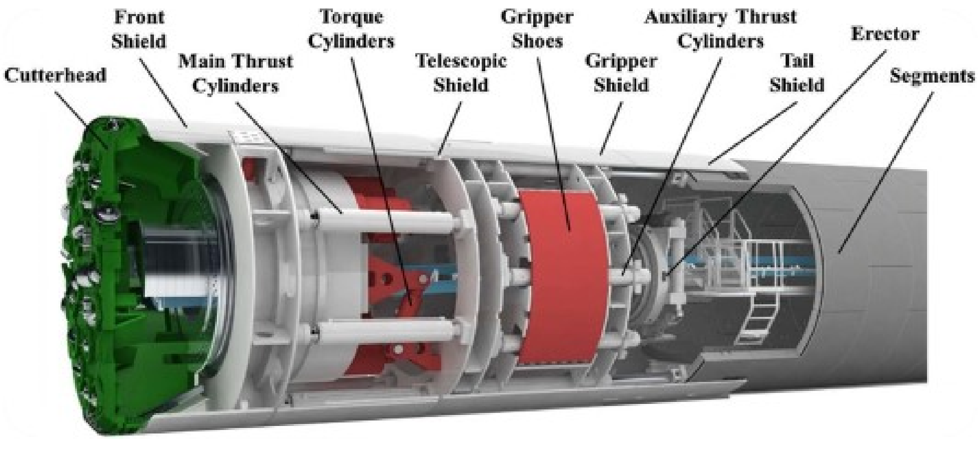


Figure 3. Double shield TBM (1- cutterhead; 2- muck ring; 3- hydraulic torque box; 4- erector; 5- thrust cylinders; 6- segmental lining; 7- belt conveyor) (Brabant and Duhme, 2017)

2.2.4 TBM Disc Cutters

One of the important factors affecting the performance of TBM is the choice of disc cutters, their number and the distance between them. Typical disc cutter sizes are 5" (127mm) to 21" (533.4mm). The choice of disc cutters is based on the technical parameters of the machine, the type of rock and the size of the cutting head. Disc cutters types are shown in Figure 4.

Figure 4. TBM disc cutters (rock-cutters.com)

2.2.5 TBM parameters

Tunnel Boring Machine has several parameters, such as thrust, torque, type of TBM, number of disc cutters, etc. Each of these parameters can affect on TBM performance.

Fukui and Okubo (2006) propose the following considerations of thrust, torque, cutting depth and tooling that are based on more than 10 tunnels data, which is the main parameters of TBM:

1. Thrust: When excavating tough rock like mudstone, the adhesive force between rock and TBM must be considered. In order to be able to subtract this force from the thrust, which is calculated from the pressure in the cylinder, it is necessary to estimate it in advance.

2. Torque: Usually data chart and motor current are the basis for torque calculation. Although a data chart must be created for a TBM-mounted motor, the data charts available are usually for

isolated motors. In this case, the motor current is subtracted from the measured motor current in the control test, while the blank test is performed when the TBM is not boring the rock, i.e., in the unloaded state.

3. Cutting depth: In the absence of the number of revolutions of the cutting head, the depth of cut can be estimated based on the rate of penetration calculated from the time of cut and tunnel distance and divided by the speed of the cutting head. But the disadvantage of this method is that the cutting time is considered even when the operation is stopped.

4. Tooling: The debris scraper, disc cutter or other tool is replaced.

2.3 ROCK MASS PROPERTIES

To correctly assess the performance of TBM, it is important to consider all aspects that affect it. In addition to the TBM parameters, the TBM performance is affected by the properties of the intact rock and the properties of the rock mass.

2.3.1 Rock Quality Designation

Rock quality designation (RQD) is an important parameter of rock mass. RQD was implemented to measure the rock mass quality in 1960s. The Table 1 shows the analysis of rock mass, where we can see that for each value of RQD there is a designation of the quality of the rock mass. For example, if RQD is equal to 30 it means that the quality of rock mass is poor. The rock quality designation (RQD) property is used to assess the fracture degree.

Table 1. Analysis of rock mass abased on RQD value (Deere, 1969)

RQD	Rock Mass Quality
<25	Very Poor
25-50	Poor
50-75	Fair
75-90	Good
99-100	Excellent

2.3.2 Rock Mass Rating (RMR)

The RMR is a rock classification system that was introduced by Bieniawki (1993) and commonly used in many countries. It consist of five (05) parameters, which are shown below. The rating scheme is detailed in Table 2.

- Strength of intact rock (UCS, point load index);
- Rock Quality Designation (RQD);
- Joint spacing;
- Joint conditions;
- Groundwater conditions.

Table 2. Rock mass rating system (Bieniawki, 1993)

(a) Five basic rock mass classification parameters and their ratings								
1.	Strength of intact rock material	Point load strength index (MPa)	> 10	4 – 10	2 – 4	1 – 2		
		Uniaxial compressive strength (MPa)	> 250	100 – 250	50 – 100	25 – 50	5 – 25	1 – 5	< 1
	Rating		*15*	*12*	*7*	*4*	*2*	*1*	*0*
2.	RQD (%)		90 – 100	75 – 90	50 – 75	25 – 50	< 25		
	Rating		*20*	*17*	*13*	*8*	*3*		
3.	Joint spacing (m)		> 2	0.6 – 2	0.2 – 0.6	0.06 – 0.2	< 0.06		
	Rating		*20*	*15*	*10*	*8*	*5*		
4.	Condition of joints		not continuous, very rough surfaces, unweathered, no separation	slightly rough surfaces, slightly weathered, separation <1 mm	slightly rough surfaces, highly weathered, separation <1 mm	continuous, slickensided surfaces, or gouge <5 mm thick, or separation 1–5 mm	continuous joints, soft gouge >5 mm thick, or separation >5 mm		
	Rating		*30*	*25*	*20*	*10*	*0*		
5.	Groundwater	inflow per 10 m tunnel length (l /min), or	none	< 10	10 – 25	25 – 125	> 125		
		joint water pressure/major in situ stress, or	0	0 – 0.1	0.1 – 0.2	0.2 – 0.5	> 0.5		
		general conditions at excavation surface	completely dry	damp	wet	dripping	flowing		
	Rating		*15*	*10*	*7*	*4*	*0*		

(b) Rating adjustment for joint orientations						
Strike and dip orientation of joints		very favourable	favourable	fair	unfavourable	very unfavourable
Rating	tunnels	0	– 2	– 5	– 10	– 12
	foundations	0	– 2	– 7	– 15	– 25
	slopes	0	– 5	– 25	– 50	– 60

(c) Effects of joint orientation in tunnelling						
Strike perpendicular to tunnel axis				Strike parallel to tunnel axis		Dip 0° – 20°
Drive with dip		Drive against dip				
Dip 45° – 90°	Dip 20° – 45°	Dip 45° – 90°	Dip 20° – 45°	Dip 45° – 90°	Dip 20° – 45°	irrespective of strike
very favourable	favourable	fair	unfavourable	very unfavourable	fair	fair

2.3.3 Q-system

According to Barton et al. (1974) the Norwegian Geotechnical Institute developed the quality index for the rock tunnelling named the Q-system. The system is an index, which determine the rock mass tunneling quality and defined by:

$$Q = \frac{RQD}{Jn} \times \frac{Jr}{Ja} \times \frac{Jw}{SRF} \quad (2.1)$$

Where, RQD is the Rock Quality Designation measuring the fracturing degree. Jn is the joint set number accounting for the number of joint sets. Jr is the joint roughness number accounting for the joint surface roughness. Ja is the joint alteration number indicating the degree of weathering, alteration and filling. Jw is the joint water reduction factor accounting for the problem from groundwater pressure, and SRF is the stress reduction factor indicating the influence of in situ stress. The Q value identifies the rock mass quality, shown in Table 3.

Table 3. Rock mass quality rating according to Q values (Barton et al., 1974)

Q-value	Class	Rock Mass Quality
400 ~ 1000	A	Exceptionally Good
100 ~ 400	A	Extremely Good
40 ~ 100	A	Very Good
10 ~ 40	B	Good
4 ~ 10	C	Fair
1 ~ 4	D	Poor
0.1 ~ 1	E	Very Poor
0.01 ~ 0.1	F	Extremely Poor
0.001 ~ 0.01	G	Exceptionally Poor

2.4 Intact Rock Properties

The properties of the intact rock are also one of the main factors affecting the performance of TBM. There are many papers, papers and studies on the relationship between rock properties and ROP of the TBM. But not all rock properties show a good correlation with ROP.

2.4.1 *Uniaxial Compressive Strength*

Rock strength should be considered first when considering the relationship between intact rock properties and rate of penetration. One of the most important parameters to consider when evaluating the progress of TBM is the uniaxial compressive strength (UCS), which also has an important influence on it. Table 4 shows the classification of rock according to uniaxial compression (UCS).

Table 4. The rock classification according to the UCS parameters (ISRM, 1978)

Category	Very low	Low	Moderate	Medium	High	Very high
UCS (MPa)	<5	5-25	25-50	50-100	100-250	>250

2.4.2 *Brazilian Tensile Strength*

Brazilian tensile strength has also influence on TBM performance as UCS. But Kumar et al. (2011) claim that BTS illustrates lower values due to micro-cracks compared to UCS. BTS is defined by:

$$\sigma_t = \frac{2P}{\pi LD} \quad (2.2)$$

Where σ_t= Brazilian tensile strength, MPa

D = diameter of the sample before testing, mm

P = maximum force on the sample before failure, N

L = length of the sample before testing, mm

2.4.3 *Cerchar Abrasivity Index*

The degree of rock abrasivity is indicated by the Cerchar Abrasivity Index (CAI). By the Table 5 we can see that the less abrasive and soft rock has the low value of CAI.

Table 5. Criteria for the CERCHAR Abrasiveness Index ASTM D7625

Classification	Average CAI Stylus Rockwell Hardness (HRC) Value 55	Average CAI Stylus Rockwell Hardness (HRC) Value 40
Very low abrasiveness	0.30-0.50	0.32-0.66
Low abrasiveness	0.50-1.00	0.66-1.51
Medium abrasiveness	1.00-2.00	1.51-3.22
High abrasiveness	2.00-4.00	3.22-6.62
Extreme abrasiveness	4.00-6.00	6.62-10.03
Quartzitic	6.0-7.0	N/A

*2.4.4 **Brittleness***

Another property of the rock that affects the performance of TBM is brittleness. This property of the rock also affects the recoverability of the rock and is very close to the crushing process (Wilfing, 2016). Morley (1944) defined brittleness as "absence of ductility". At the moment it is difficult to determine what exact impact brittleness has on TBM performance. Yagiz (2009) introduces a brittleness index which is based on a punch penetration test and expresses an equation showing brittleness as a function of UCS, BTS and density:

$$BI = (0.198 \times \sigma_c) - (2.174 \times \sigma_t) + (0.913 \times \rho - 3.807) \quad (2.3)$$

According to Yagiz (2009) if we consider the density and strength at the same time, then the correlation coefficient $r2$ = 0.94, which is a good indicator. Table 6 shows the brittleness classification.

Table 6. Brittleness classification (Yagiz 2009).

Yagiz's brittleness, BI_1 (kN/mm)	Brittleness class
≥40	Very high brittle
35-39	High brittle
30-34	Medium brittle
25-29	Moderate brittle
20-24	Low brittle
≤19	No-brittle (ductile)

2.5 TBM performance prediction models

The NTNU model was developed at the Norwegian University of Science and Technology. The NTNU model calculates the prediction of penetration rate and estimates the cutter life by using empirical data. According to Macias (2016) this model is widely used in the industry due to advantages and frequently updates.

Bruland (2000) developed the NTNU model and presented influential factors (geological and machine parameters) on net penetration rate. Geological parameters: fracture frequency, fracture orientation, drilling rate index, porosity. Machine parameters: gross average cutter thrust, cutterhead velocity, TBM diameter, cutter spacing, shape and size. The basic net penetration rate can be calculated from following equation:

$$I_0 = i_0 \times RPM \times \left(\frac{60}{100}\right) \quad (2.4)$$

where, I_0 – main penetration rate (m/h), i_0 – previously estimated penetration rate (mm/rev), RPM – cutterhead speed (rev/min).

Macias (2016) improved the Bruland (2000) NTNU model. He increased the empirical data basis by including the new project data. Macias (2016) made improvements by updating, extending or revising the factors such as cutter diameter, number of cutter, cutterhead power, cutterhead velocity, DRI calculation intervals, and etc. The basis net penetration rate by Macias (2016):

$$I_0 = i_0 \times RPM \times \left(\frac{60}{100}\right) \times k_{RPM} \quad (2.5)$$

where, I_0 – basic penetration rate (m/h); i_0 – basic penetration rate (mm/rev); RPM – cutterhead speed (rev/min); k_{RPM} – correction factor for applied cutterhead rpm.

Rostami (1997) developed the Colorado School of Mines (CSM) model which was established by Ozdemir et al. (1977). This model was created to analyze the penetration rate. "The philosophy behind this model is to first start from the individual cutter forces acting on the rock mass, then determine the overall cutterhead thrust- and power requirements to obtain the maximum rate of penetration" (Rostami & Ozdemir, 1993). Rostami (1997) provided the formula for total force per cutter:

$$F_t = \frac{T \times R \times \varphi \times P}{(1+\psi) \times 1000} \quad (2.6)$$

Where, F_t – total forces applying on disc (kN/cutter), T – cutter tip width, R – cutter radius (mm), φ – angle of contact (rad), P – pressure of contact area (MPa), ψ - stress distribution factor (usually between 0.2 to -0.2).

Yagiz (2002) introduced the modified CSM. This model calculate rate of penetration based on a brittleness index, the angle and distance between the weakness planes. The ROP from MCSM can be calculated as:

$$ROP = 0.272 + (0.027 \times BI) - (0.225 \times F_s) + (0.437 \times \log(\alpha)) + (0.097 + CSM_{ROP}) \quad (2.7)$$

Where ROP – rate of penetration (m/h), BI – predicted brittleness (kN/mm), F_s – distance between planes of weakness (m), α – angle between the plane of weakness and TBM driven direction (degree).

Barton (2000) introduced Q_{TBM} model based on Q – system, which is described previously. Barton (2000) modified Q_0 to a tunnelling oriented direction and by adding the other parameters Q_{TBM} was presented by following formula:

$$Q_{TBM} = Q_0 \times \frac{SIGMA}{\frac{F^{10}}{20^9}} \times \frac{20}{CLI} \times \frac{q}{20} \times \frac{\sigma_\theta}{5} \quad (2.8)$$

where, $Q_0 = \frac{RQD_0}{Jn} \times \frac{Jr}{Ja} \times \frac{Jw}{SRF}$, $SIGMA$ – rock mass strength which can be divided by favorable/unfavorable inclination values; F – net thrust per cutter ($tnf/cutter$); CLI – cutter life index; q – quartz content (%); σ_θ – biaxial stress on tunnel face (MPa).

Net penetration rate (NPR) by using Q_{TBM}:

$$NPR \approx 5 \times Q_{TBM}^{-1/5} \quad (2.9)$$

Yagiz (2008) presented the more precise and accurate equation to predict the penetration rate. This predictive equation was based on Queens tunnel and was adapted for faulted or jointed hard rock:

$$ROP = 1.093 + 0.029 \times PSI - 0.003 \times UCS + 0.437 \times \log(\alpha) - 0.219 \times DPW \quad (2.10)$$

Where PSI - peak slope index (kN/mm), UCS - uniaxial compressive strength (MPa), α - smallest angle between tunnel axis and discontinuity (degree), DPW - distance between planes of weakness (m).

2.6 Cutting force estimation models

The rock cutting force is the main parameter of tunnel boring machine, which affects on its performance directly. This parameter was used as input parameter for several laboratory research and field studies to develop the prediction model for penetration rate.

Gehring (1995) introduced the following equation by using the 6 correction factors to predict the penetration rate:

$$p = \frac{F_N}{UCS} \times k_i \quad (2.11)$$

Where, p – penetration rate (mm/rev), F_N – net thrust per cutter (kN/cutter), UCS – uniaxial compressive strength (MPa), k_i – correction factor (k_0, k_1, k_2, k_3, k_4, k_5)

A correction factor k_i consist of: k_0 – basic penetration; k_1 – specific failure power; k_2 – rock mass material; k_3 – state of stress in rock mass; k_4 – cutter diameters; k_5 – cutter spacing.

According to laboratory studies by Sanio (1986), cutting forces are reduced significantly in the presence of rock joints, with the exception of joints oriented perpendicular (normal) to the cutting surface.

Nelson et al. (1983a, 1985) have compared instantaneous penetration rates with rock properties based on various tunneling designs. They state that compressive or tensile strength, fracture toughness, PLI (Point Load Index) are not related to penetration rate. On the other hand, their research shows that ROP and Field Penetration Index (FPI) have a good correlation.

Rostami (1997) introduces the force estimation formulas based on database of disc cutting forces by using the full scale cutting tests. The formula with linear relationship is dimensionally incorrect. The linear relationship for the normal force estimation is as follows:

$$F_N = -31620 + 2182 \times S + 5538 \times P + 2.6 \times \sigma_t + 0.357 \times \sigma_c + 71621 \times T + 1162 \times R \quad (2.12)$$

Where: F_N – Normal Force (lbs), S – Spacing (in), P – Penetration (in), σ_t – Tensile Strength (Psi), σ_c – Uniaxial Compressive Strength (Psi), T – Tip Width (in), R – Cutter Radius (in).

The relationship includes power functions in logarithmic analysis which lead to dimensionally correct equation (Rostami, 1997):

$$F_N = 8.76 \times T^{0.797} \times R^{0.788} \times \Phi^{0.602} \times S^{0.28} \times \sigma_c^{0.629} \times \sigma_t^{0.195} \quad (2.13)$$

Rostami (1997) modified this dimensionally correct equation to obtain the correct dimensions and presented the following equation:

$$F_N = T \times R \times \Phi \times P_r \quad (2.14)$$

Where P_r – Pressure (psi).

According to equations above Rostami (1997) made the plot of predicted versus measured normal forces which are shown in Figures 5 to 7.

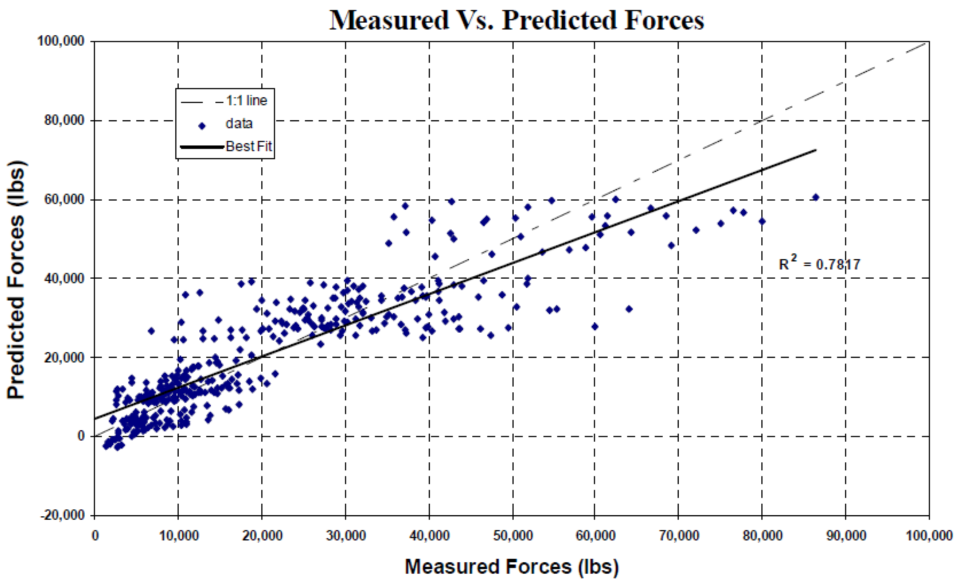


Figure 5. Comparison for linear equation (Rostami, 1997).

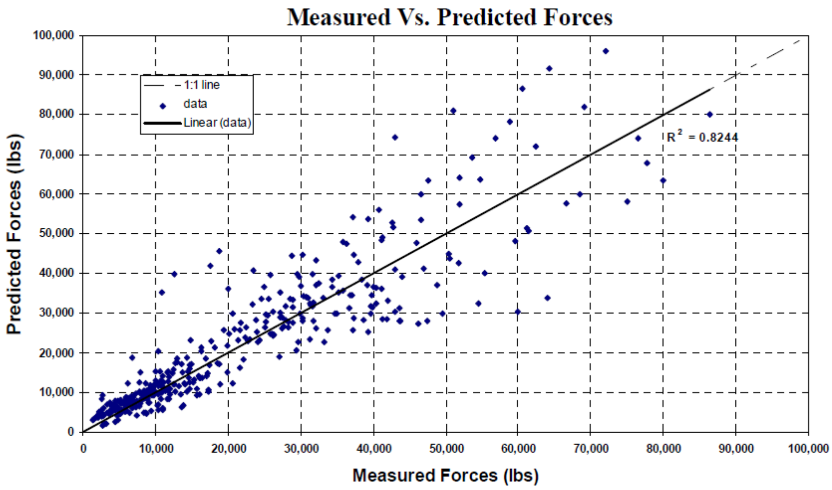


Figure 6. Comparison for Logarithmic equation (Rostami, 1997).

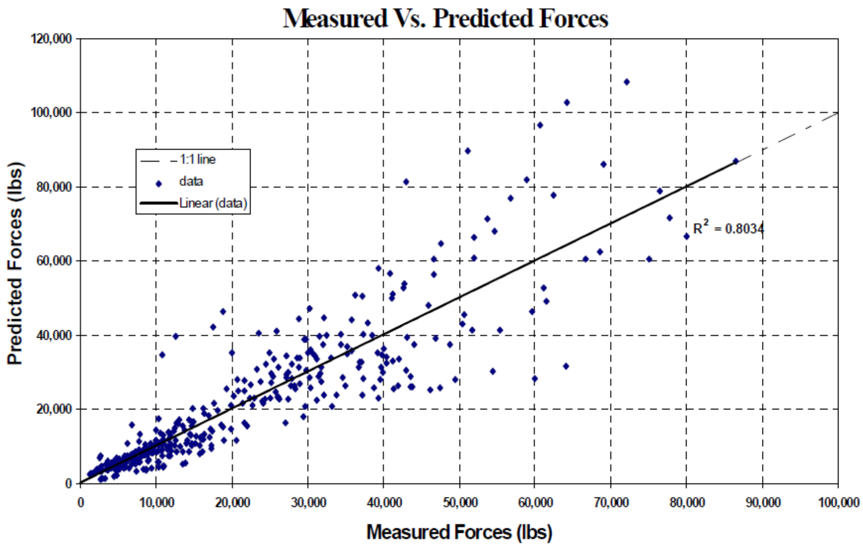


Figure 7. Comparison for dimensionally corrected equation (Rostami, 1997).

Rostami (1997) also develop the graphs with relation the predicted normal force, based on cutting force estimation formulas, and rock parameters, such as UCS, BTS, and other, which are shown in Figure 8 and 9. "The forces increase with compressive strength of the rock assuming that all other cutting parameters remain the same. For a given rock compressive strength, the cutting forces increase at a lower rate with tensile strength" (Rostami, 1997).

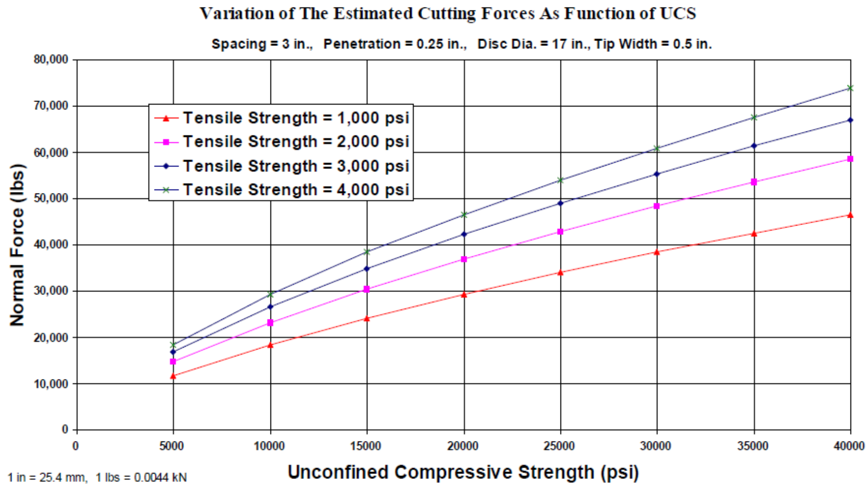


Figure 8. Variation of predicted normal forces as a function of UCS (Rostami, 1997).

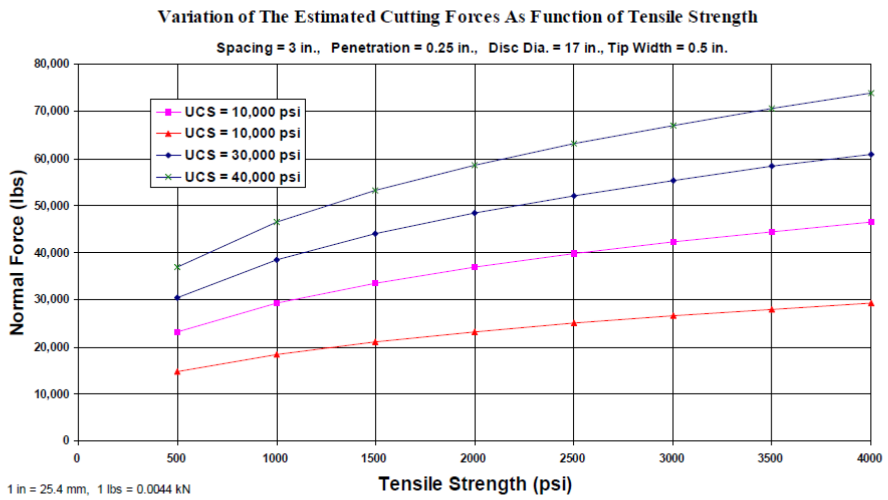


Figure 9. Variation of predicted normal forces as a function of tensile Strength (Rostami, 1997).

Rock Joint Rate (RJR) is a new method for predicting rate of penetration of tunnel boring machines (TBM) in hard rock conditions. The combination of operational and geological data, which was obtained from tunnel data excavated in sedimentary and igneous rocks, became the basis for this RJR model (Maleki, 2018). The tunnel diameter, geological condition, and TBM drilling parameters were used as inputs to this method. Maleki (2018) claims that the principle geological parameters are characteristics of discontinuities along the tunneling axis, such as orientation, aperture, frequency, spacing and number of the joints, and uniaxial compressive strength (UCS). The characteristics of discontinuities describe the influence of the joints and fractures in the rock mass. As major TBM's operational parameters the cutterhead rotation speed (RPM) and the machine thrust force were chosen. In the Maleki (2018) study, the influence of each joint property on the determination of machine rate of penetration was studied separately. Maleki (2018) maintain that the tunnel route should be divided into structurally similar and lithologically zones based on this method. Afterward, joints should be mapped with the help of the scanline method both perpendicular and parallel to the tunnel axis. Maleki (2018) also say that the use of random window mappings is necessary in eroded rock zones to research the geometric features of joints. Moreover, faults, large gaps and crushing zones are studied individually (Maleki, 2018). Maleki, (2018) concludes that the most important parameter for hard rock in TBM is the average thrust force per disc cutter.

Yagiz et al. (2021) claim that the Linear Cutting Machine (LCM) test is one of the most effective laboratory tests for evaluating the cutting ability of rocks. Rock mass blocks are used to measure cutting force instead of intact rocks, because intact rocks are not mass features. Rocks on which studies were carried out: dolerite, granitic gneiss, meta-dolerite, calc-silicate, meta-andesite and paragneiss. Moreover, intact rock tests were conducted on density, Cerchar abrasivity index, brittleness, tensile strength and uniaxial compressive strength. Afterwards, the relationship between LCM testing cutting force and intact rock properties has been studied (Yagiz et al., 2021). Cutting force measurements were taken in normal, rotating and lateral dimensions. Yagiz et al. (2021) maintains that to obtain the best result of the relationship between the cutting force of the rock and the properties of the rock, static analyzes were carried out, such as non-linear and linear regression analysis, multiple and simple analysis.

Yagiz et al. (2021) also says that a simple statistical analysis of rock properties (BI, CAI, BTS, UCS, depth of cut (d)) performed showed that depth of cut and CAI do not have a large effect on cutting force, while BI and UCS have a large influence on cutting force. Since d and CAI affect tool consumption and cutting force but do not show good relationships with cutting force of Constant Cross Section (CCS) disc cutter, both parameters can be used in multiple non-linear and linear regression analyzes to find their effect on specific energy and cutting force. Figures 10 to 13 show the relations of inputs (UCS, CAI, BI, depth of cuts (d)) and output (Fn).

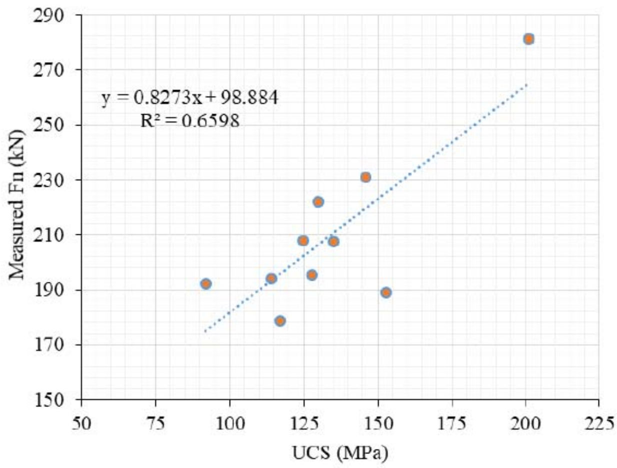


Figure 10. Relations between measured Fn and UCS (Yagiz et al., 2021).

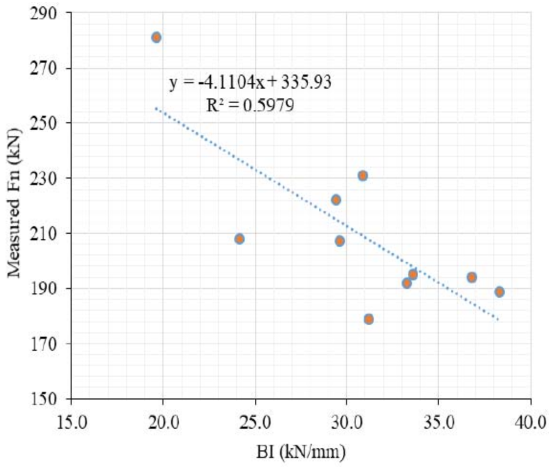


Figure 11. Relations between measured Fn and BI (Yagiz et al., 2021).

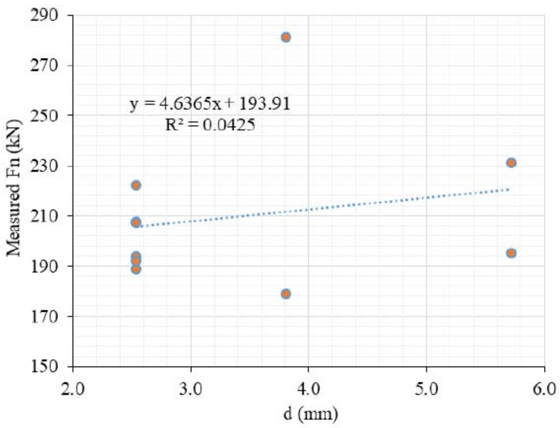


Figure 12. Relations between measured Fn and d (Yagiz et al., 2021).

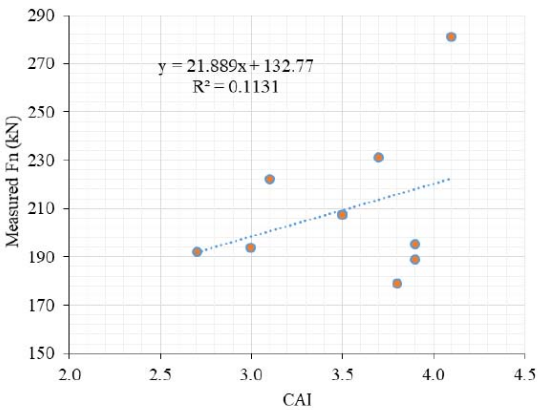


Figure 13. Relations between measured Fn and CAI (Yagiz et al., 2021).

The method of multiple linear or non-linear regression analysis is a common technique in engineering studies to estimate unknowns based on known parameters (Yagiz et al., 2021). Based on the method of multiple non-linear regression analysis, it was found that in order to determine the ratio of cutting force and rock properties, such as CAI, UCS, BI, depth of cut, it is necessary to take a high coefficient of determination. However, according to Yagiz et al. (2021) the results obtained are valid for the same rock type and data range used in the data set. The equation to estimate normal force (Fn) by UCS, CAI, BI and d is shown below:

$$F_n = 1.105 \times UCS - 2.113 \times BI - 50 \times CAI + 7.6 \times d + 276.4 \quad (2.15)$$

Yagiz et al. (2021) conclude that “Fn could be estimated as a function of rock properties and depth of cut”. They also show the relation between measured normal force and predicted normal force (Figure 14).

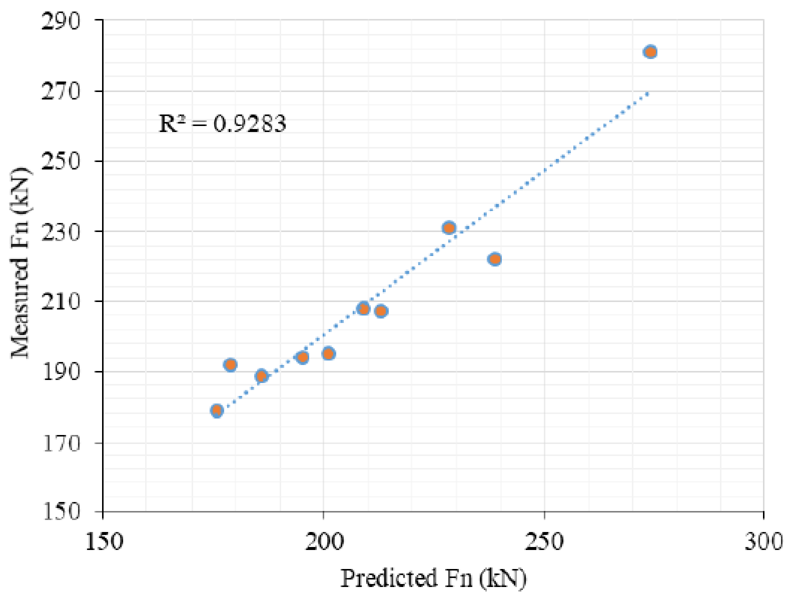


Figure 14. Relations between measured Fn and predicted Fn (Yagiz et al., 2021).

The basis for the method of calculating the strength of rocks in the face from the cutting force created by TBM was the results of experiments in the laboratory (Fukui and Okubo, 1999). A good relation was found between the strength of the rock, estimated from the cutting force, the rebound hardness of the Schmidt hammer, and other rock properties. Fukui and Okubo (2006) claim that this method allows you to control the strength of rocks in real time. Fukui and Okubo (2006) note that evaluating the strength of rocks by cutting force is one way to avoid errors associated with the human factor. Fukui and Okubo (2006) accepted the statement that the thrust force is proportional to cutting depth and defined the following formulas to thrust (F) and torque (T):

$$F = c_1 \times \sigma_c \times p \quad (2.16)$$

$$T = c_2 \times \sigma_c \times p^{1.5} \quad (2.17)$$

Where σ_c – rock strength, p – cutting depth.

Fukui and Okubo (2006) plotted the graph with relationship between torque/thrust and penetration rate based on Hiraya tunnel, which is shown in Figure 15.

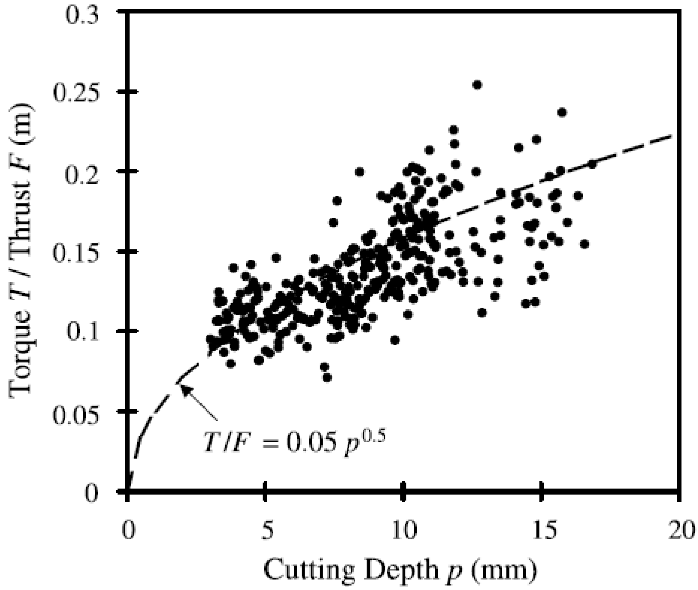


Figure 15. Relationship between torque/thrust and penetration rate (Fukui and Okubo, 2006).

Fukui and Okubo (2006) compared data from two types of tunnels, with granite and with mixed strata which is consist of several rock types. A good correlation was found between the results of the geological study and the calculated strength of the rock, which was estimated from the cutting force. Rock classification can be predicted by rock strength with a reasonable level of confidence (Fukui and Okubo, 2006). Fukui and Okubo (2006) summarized in their study the key aspects that determine the strength of the rock using cutting force data. TBM parameters such as torque, cutter head speed, thrust and depth of cut are often taken as a mean average for the entire tunnel or for various classifications of the rock mass (Jodl and Stempkowski, 2020). Fukui and Okubo (2006) investigated the changes in operating conditions throughout the duration of the tunnel excavation. The stability of the tunnel is significantly affected by the joints contained in the rocks, depending on their size and density (Fukui and Okubo, 2006). They tested chainages of 2 tunnels (Hiraya and Shinyuyama) to show the influencers of penetration rate. Figures 16, 17, 18 illustrate the results of testing parameters. Fukui and Okubo (2006) conclude that torque and thrust exceeds the set limit because of harder rock. They also noted that the excavation of brown andesite requires less thrust and torque than black andesite.

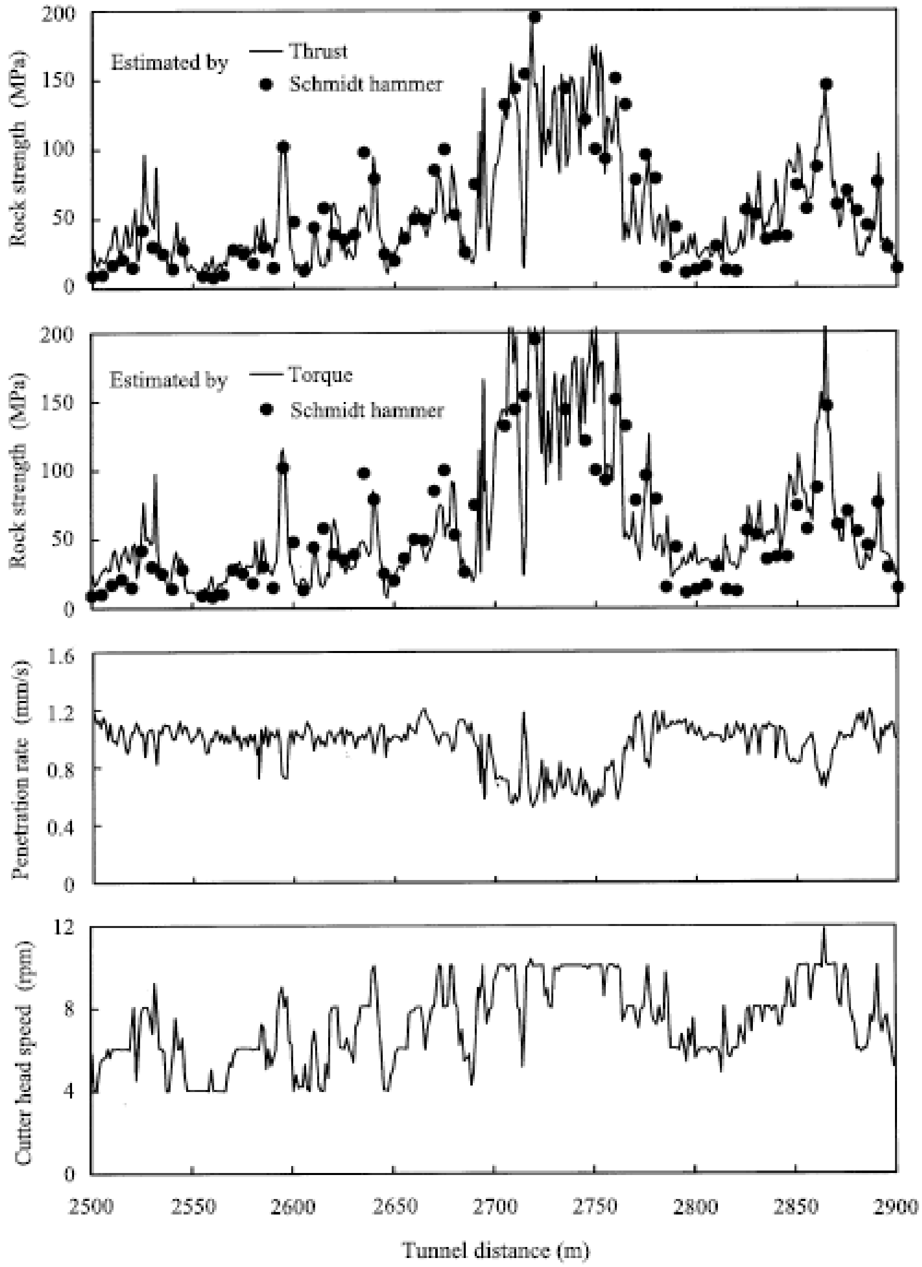


Figure 16. Rock mass classification, rock strength, penetration rate and cutter head speed (Hiraya Tunnel) (Fukui and Okubo, 2006).

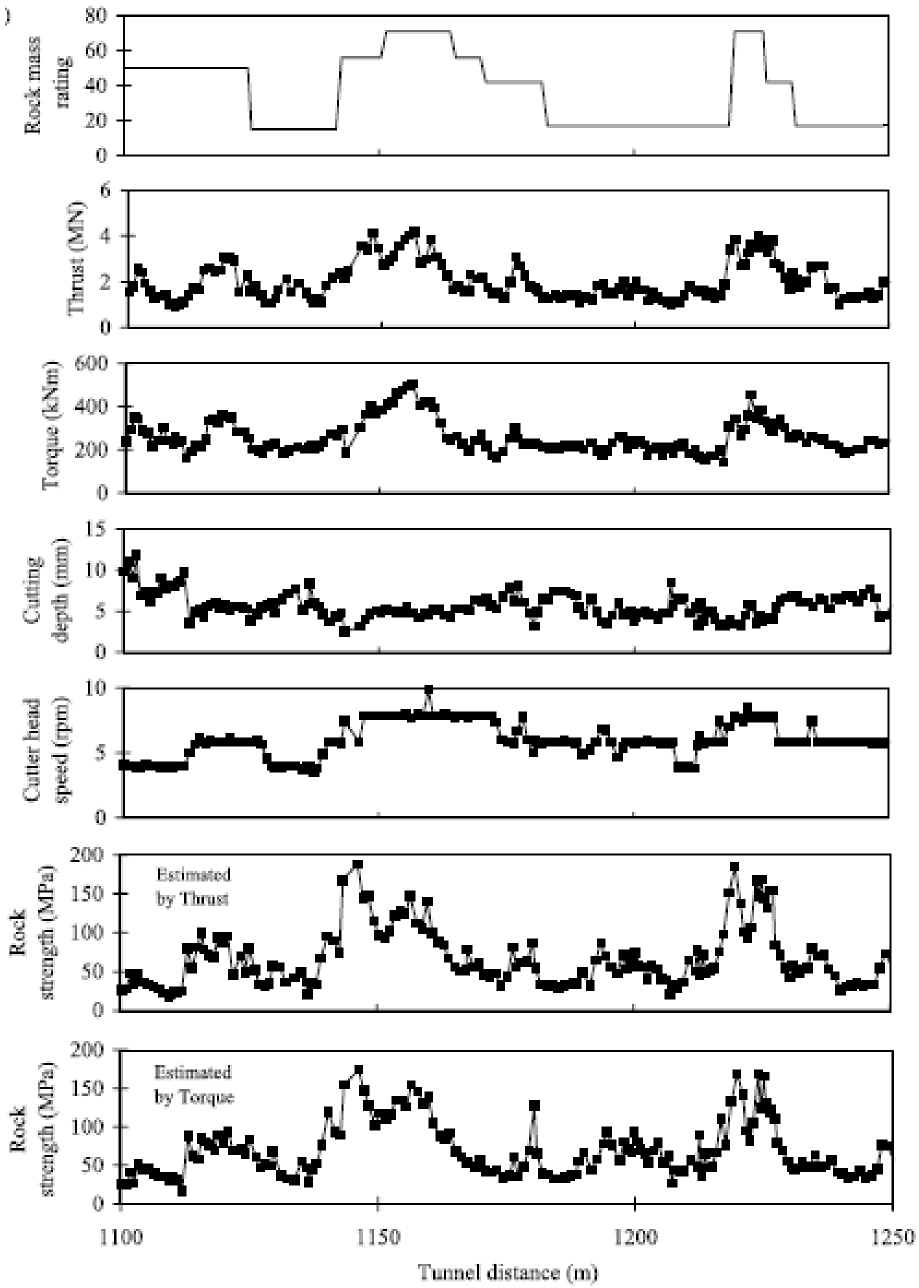


Figure 17. Changes in operating conditions and rock strength with tunnel distance (Shinyuyama Tunnel – black andesite) (Fukui and Okubo, 2006).

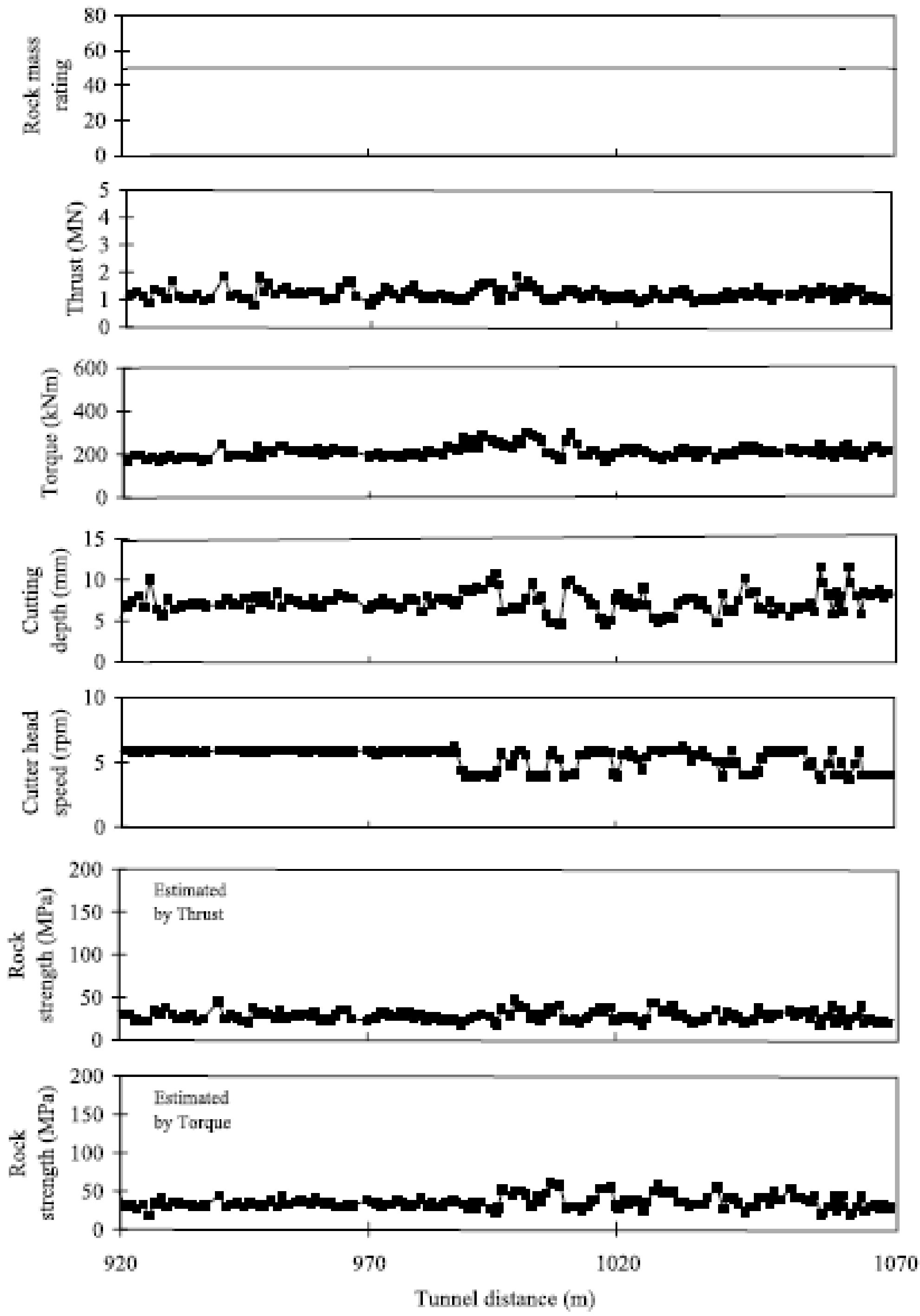


Figure 18. Changes in operating conditions and rock strength with tunnel distance (Shinyuyama Tunnel – brown andesite) (Fukui and Okubo, 2006).

Hassanpour et al. (2011) investigated and analyzed geological data and TBM parameters based on projects with different rock types. Based on these results, Hassanpour et al. (2011) developed an empirical-based Rate of Penetration (ROP) Field Penetration Index (FPI) equations:

$$FPI = e^{((0.008\times UCS)+(0.015+RQD)+1.384)} \quad (2.18)$$

Where FPI - field penetration index (kN/cutter/mm/rev), UCS - uniaxial compressive strength (MPa), RQD - rock quality designation (MPa).

Further, ROP calculated by following equation:

$$ROP = \frac{0.06\times F_N \times RPM}{FPI} \quad (2.19)$$

Where F_N - average disk cutter load (kN), RPM – rotational speed (rev/min).

Hassanpour et al. (2015) provides simple model for estimating hard rock TBM performance and cutter life under several geological conditions. This model, which is aimed to calculate the penetration rate, is based on machine parameters (RPM and average cutting head thrust) and rock properties (RQD and UCS). Hassanpour et al. (2015) also offers the formulas for disc cutter life estimation as a function of Vickers Hardness Number Rock (VHNR) and Uniaxial Compressive Strength (UCS). A set of abrasivity and boreability classifications based on the characteristics of rock mass has also been introduced so that the field penetration index (FPI) can be predicted to estimate the rate of penetration and volume of excavated rock at each cutter change to determine cutter life. Ground conditions were classified in Boreability classes: Tough, difficult boring; Fair; Good; Very good, easy boring, potential support problems; Good, easy boring, potential support problems; May be Problematic, shielded tunneling. 7 abrasivity classes for ground types: Extremely abrasive, High cutter wear; Very abrasive; Abrasive; Moderately abrasive; Slightly abrasive; Not very abrasive; Non-abrasive, almost no cutter wear (Hassanpour et al., 2015). Hassanpour et al. (2015) conclude that the main criterion for effective prediction of the TBM performance is the similarity of the geological database, which is used to construct the predictive equations, with the geological conditions of the projects. Although models of the site-specific are naturally better for predictive purposes, an estimate of the potential performance of TBM with sufficient accuracy for other cases can be obtained by extending the use of the proposed equations (Hassanpour et al., 2015).

There are also many estimation models related to cutting force, which are shown in Table 7.

Table 7. Existing TBM cutting force models

Empirical equations/models	References
$PRev = 3940 \times F_n / UCS$	Graham, 1976
$PRev = 624 \times F_n / TS$	Farmer & Glossop, 1980
1. $F_{normal}/\sigma_c = 0.15 \times p - 0.21$ 2. $F_{rolling}/\sigma_c = 0.027 \times p - 0.07$	Snowdon et al., 1982
$P = (F_n / UCS) \times k_i$	Gehring, 1995
1. $F_N = -31620 + 2182 \times S + 5538 \times P + 2.6 \times \sigma_t + 0.357 \times \sigma_c + 71621 \times T + 1162 \times R$ 2. $F_N = 8.76 \times T^{0.797} \times R^{0.788} \times \Phi^{0.602} \times S^{0.28} \times \sigma_c^{0.629} \times \sigma_t^{0.195}$ 3. $F_N = T \times R \times \Phi \times P_r$	Rostami, 1997
1. $F = c_1 \times \sigma_c \times p$ 2. $T = c_2 \times \sigma_c \times p^{1.5}$	Fukui & Okubo, 2006
$BI = BI1 \times p^{-0.75} = F_n / p$	Gong & Zhao, 2009
$ROP = 0.06 \times F_N \times RPM / FPI$	Hassanpour et al., 2011
$p = ((F_n - b_{BTS/LBC}) / UCS) \times k_0 \times k_2 \times k_i + 3$	Wilfing, 2016
$F_n = 1.105 \times UCS - 2.113 \times BI - 50 \times CAI + 7.6 \times d + 276.4$	Yagiz et al., 2021

Note: For more detailed information please refer to references.

$PRev$ – penetration per revolution, F_n , F_{normal} – cutting normal force, UCS – uniaxial compressive strength of intact rock, TS – tensile strength, σ_c – rock strength, p – cutting depth, P – penetration rate (mm/rev), k_i – correction factor (k_0, k_1, k_2, k_3, k_4, k_5), FN – Normal Force (lbs), S – Spacing (in), P – Penetration (in), σ_t – Tensile Strength (Psi), σ_c – Uniaxial Compressive Strength (Psi), T – Tip Width (in), R – Cutter Radius (in), Pr – Pressure (psi), BI – brittleness, F – Thrust, T – Torque.

2.7 Limitations of the models in the literature

Most of the equations and models described in the literature that are related to predicting the performance of a tunnel boring machine depend on the results of tests of intact rock and machine parameters or on large-scale tests of a rock cutter. There are several limitations to existing models for predicting the cutting force of tunnel boring machines (TBMs):

1. Insufficient accuracy: Some prediction models may have limited accuracy in forecasting TBM cutting force due to difficulties in modeling complex geological conditions.
2. Limited data: Prediction models may be limited by insufficient data, particularly in cases where TBMs are used in new or poorly studied geological conditions.
3. Inability to account for all factors: Models may be unable to account for all factors influencing TBM cutting force, such as TBM rotation speed, cutter head type, and so on.
4. Calibration requirements: Prediction models may require calibration for a specific TBM, which can be difficult and costly.
5. Variable conditions: Tunnel conditions may change during excavation, which can affect TBM cutting force and complicate forecasting.
6. Interaction with the environment: TBM operation can affect the surrounding environment, including soil and water, which can affect cutting force and complicate prediction.

Given these limitations, it is important to consider data quality and model accuracy when choosing a method to use.

2.8 Research Approach

The research approach used in this thesis involved developing a new cutting force estimation model for tunnel boring machines using multilinear and non-linear regression analysis based on statistical analysis in Python. The aim was to investigate the relationships and influences between various TBM properties (such as type, power, torque, thrust force, rolling force, cutter load, number of cutters, and utilization) and intact rock properties (including Brazilian tensile strength, uniaxial compressive strength, density, and Cerchar Abrasivity Index) or rock mass properties (such as Rock Mass Rating, Q-system, Rock Quality Designation, dip direction, and joint spacing).

2.9 Discussion

The literature review of studies related to cutting force of the tunnel boring machine show that extensive research of this subject is necessary. "In general, these investigations are useful in identifying some of the influencing parameters, but they cannot directly address the cutting force generation and offer an analytically developed closed form solution" (Rostami, 1997). Similarly, field measurements on a tunnel boring machine do not provide a solution for estimating cutting forces, as they include geological conditions and the complexity of mechanical systems. Crushing zones, their behavior and development also remain unstudied. Based on existing models related to cutting force, it can be concluded that in most cases, the cutting force is influenced by the rock strength. It means that in many cases we can predict time and energy consumption for cutting force according to these models.

3. CUTTING FORCE ESTIMATION

3.1 INTRODUCTION

All available and relevant data for this study were collected from actual drilling data and from the literature through journal articles and industry scientific reports. The most appropriate data for our method were selected from six projects where the Tunnel Boring Machine was used (Queens Tunnel, Manapouri Tunnel, Milyang Tunnel, Iranian Tunnels, US Tunnels, and Italian Tunnels). They turned out to be data from Iranian tunnels (Zagros, Ghomrood and Karaj). Further, the values, which were measured in all tunnels and are the main parameters of rocks and TBM, were identified. After obtaining the data set and calculating the corresponding parameters, Python (Jupyter) statistical analysis was used to establish possible correlations between the cutting force and the properties of the intact rock and the properties of the rock mass.

The data collected from Iranian projects and literature was combined into an Excel file, which was revised and updated during this project as new data was included, which may have changed our interpretation of data already included in the Excel file. For example, incomplete datasets consisting only of drilling rates and rock properties sometimes helped us better understand other, more complete datasets. However, in some cases, data on the properties of the rock or the parameters of the drilling machine were simply not enough. In this case, ignoring this data was the best option. Also, some data was predicted using the imputation method IterativeImputer.

IterativeImputer is a statistical analysis technique used for imputing missing values in datasets. It is implemented in Python as part of the scikit-learn library, which is a popular statistical analysis library. The IterativeImputer algorithm works by using a round-robin approach to impute missing values. It iteratively estimates the missing values based on observed values in the dataset, and then uses these estimates as imputations for the missing values in subsequent iterations. This process continues for a specified number of iterations or until convergence is achieved. Unfortunately, this method sometimes shows non-realistic values in some datasets as Manapouri tunnel dataset. But we need to impute our missing values so as not to lose a large number of other meaningful values.

Depending on the type of information needed for the purposes of this study, data was collected from various sources, including journal articles, scientific projects, and technical reports, but the main source is existing project data that was actually measured. Based on the database created in this dissertation, the data presented for cutting force are of good quality. Therefore, the results of regressions performed with statistical analysis showed more reliable and better results. Since we will later be interested in concepts such as uniaxial compressive strength, Brazilian tensile strength and density are the rock properties for which data were collected in this study. Our statistical processing of the data will allow us to offer a more general description of how rock properties and machine parameters affect cutting force efficiency.

3.2 AN OVERVIEW OF STATISTICAL ANALYSIS APPROACH

Statistical analysis has become a popular approach for data analysis and prediction due to its ability to handle large, complex datasets and to automatically identify patterns and relationships within the data. This can be used to develop predictive models that can be used to make decisions, identify trends, or forecast future outcomes.

There are various techniques in statistical analysis that can be used for data analysis and prediction. One of the most common technique is Regression Analysis. This technique involves finding the relationship between two or more variables by fitting a line or curve to the data. Regression analysis can be used to predict future values of a variable based on past data.

One of the primary uses of statistical analysis is to find correlations between variables in a dataset. Correlations can help us understand the relationship between variables and identify patterns in the data. Statistical analysis algorithms can be used to find correlations between variables in the data, even when the relationship is complex and nonlinear.

Regression analysis is a statistical technique used to find the relationship between two or more variables. It involves fitting a line or curve to the data and using this line or curve to predict future values of the dependent variable. Regression analysis can be used for simple linear regression, multiple linear regression, and nonlinear regression.

Simple linear regression involves finding the relationship between two variables, where one variable is the dependent variable and the other variable is the independent variable. Multiple linear regression involves finding the relationship between multiple independent variables and a single dependent variable. Nonlinear regression involves finding the relationship between variables that do not follow a linear pattern.

For nonlinear regression analysis I used Trust Region Reflective (TRF). TRF algorithm is a type of constrained optimization algorithm that iteratively updates the parameters of the regression model in order to minimize the residual sum of squares (RSS) between the predicted values and the observed values. The algorithm uses a trust region approach, where it restricts the step size of parameter updates within a certain region around the current parameter estimates. This helps in preventing the algorithm from taking overly large steps that may lead to divergence or overshooting the optimal parameter values.

For regression analysis we need to import the necessary libraries for data manipulation, visualization, and regression analysis in Python, such as pandas, numpy, matplotlib, and scikit-learn. After that, load the dataset into a panda DataFrame and perform any necessary data preparation, such as handling missing values, converting data types, and splitting the dataset into independent variables (X) and dependent variable (y). Further, we implemented simple linear, multilinear or non-linear regression analysis and developed the prediction model.

Statistical analysis is a tool for data analysis and prediction. It involves using statistical models and algorithms to enable computers to learn from data and identify patterns and relationships within the data. Statistical analysis techniques such as regression analysis can be used to find correlations between variables in the data and to develop predictive models that can be used to make decisions and forecast future outcomes.

3.3 IRANIAN TUNNEL PROJECTS

Data was collected according to Iranian tunnel projects which consist of the Zagros water conveyance tunnel, the Ghomrood water conveyance tunnel and the Karaj water conveyance tunnel.

The Zagros water conveyance tunnel (ZWCT) is a 49 km tunnel designed to convey 70 m3/s of water from Sirvan River to Dashte Zahab plain in western Iran. The tunnel is divided into three lots: 1A, 1B, and 2. As of November 2014, approximately 22 km of Lot 2 (out of a total length of 26 km) has been excavated using two double shield tunnel boring machines (TBMs) from both southern and northern portals. The bored section of the tunnel passes through various geological units belonging to the three main formations of Zagros Mountain ranges, which mainly consist of weak to moderately strong argillaceous-carbonate sedimentary rocks.

The Ghomrood water conveyance tunnel is a component of a larger water conveying system that transfers 23 m3/s of water from the Dez river basin to the Ghomrood river basin, supplying drinking water to various cities in central Iran. The tunnel spans 36 km in total and has a boring diameter of 4.525 m, with a finished diameter of 3.8 m. In this project double shield machine and EPB-Hard rock machine were used. The Ghomrood water conveyance tunnel is situated in the Sanandaj-Sirjan zone (SSZ), which is a prominent geological zone in Iran. The SSZ is characterized by being a metamorphic belt that spans approximately 1500 km from northwest

(Sanandaj) to southeast (Sirjan), running parallel to the Zagros Fold Thrust belt. It has a width of 150-200 km. The tunnel alignment primarily consists of an alternating sequence of Jurassic sandstones and shales, with some areas exhibiting metamorphosed rocks such as metasandstones, slates, phyllites, graphite schists, and quartz schists. Additionally, there are quartzite veins and Cretaceous carbonate rocks present along the alignment of the tunnel.

The Karaj Water Conveyance Tunnel (KWCT) has been designed to transfer 16 m3/s of water from the Karaj (Amir-Kabir) Dam to Tehran metropolitan area. The tunnel is approximately 30 km long with a boring diameter of 4.65 m. A double shield type TBM was chosen to excavate the entire length of the tunnel. The predominant geological unit in the project area is the Karaj formation, which is a well-known formation of the Alborz Mountains. The Karaj formation is composed of various pyroclastic rocks, often interbedded with sedimentary rocks. The main rock type in the formation is green vitric to crystal lithic tuff, but other types of tuffs such as tuff breccias, sandy and limy tuffs, as well as limestones, shales, siltstones, and sandstones are also present.

3.4 DATA DESCRIPTION

The information utilized includes 11 input parameters, which consist of 2 TBM parameters, 4 properties of intact rock, and 5 properties of rock mass. Table 8 outlines these datasets and presents the highest, lowest, average, and standard deviation values for various rock characteristics, such as Average Thrust, Power, Utilization factor, UCS, BTS, Quartz Content, CLI, Spacing, RQD, Basic RMR, Q-system, GSI, and rate of penetration (ROP). Table 9 shows the first 20 rows of dataset (see Appendix 1 for whole data). Figure 19 shows the histograms showing the global distributions of cutting force. The mean value for Thrust is 5093.87 kN, as shown in Figure 19.

Table 8. A description of Iranian tunnels project.

Parameters	*N*	*Minimum*	*Maximum*	*Mean*	*Std.Deviation*
Average Thrust (kN)	107	2510.0	7790.0	5093.87	1252.84
Power (kW)	107	208.0	970.0	629.42	190.83
U (%)	107	3.17	45.12	24.64	8.43
UCS (MPa)	107	20.0	170.0	68.64	41.94
BTS (MPa)	107	4.7	9.9	6.94	1.48
Quartz Content (%)	76	1.0	30.0	9.07	8.25
CLI	76	50.0	98.4	72.17	13.8
Spacing (cm)	107	0.025	0.8	0.27	0.18
RQD (%)	107	10.0	100.0	59.96	25.85
Basic RMR	107	25.71	76.26	53.03	11.52
Q-system	107	0.11	53.3	8.89	12.86
GSI	107	15.0	85.0	50.89	17.82
ROP (m/h)	107	1.94	20.89	9.11	3.78

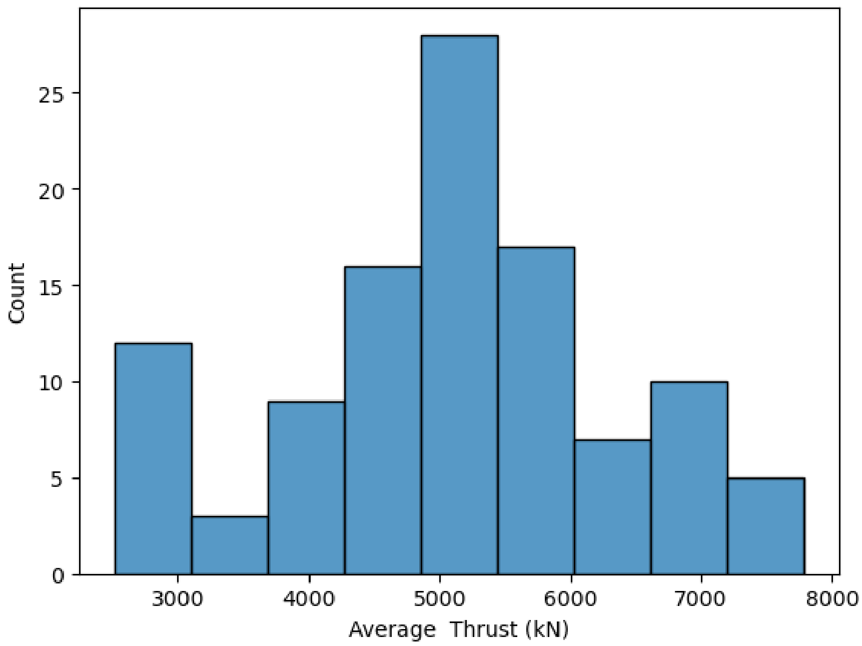


Figure 19. Cutting force distribution graph of Iranian tunnels.

Table 9. First 20 rows of Iranian tunnels project dataset.

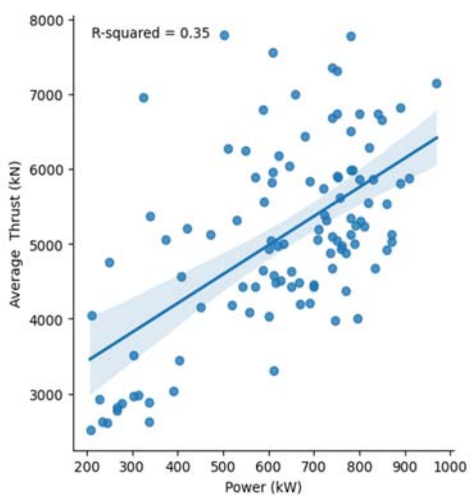
Average Thrust (kN)	Power (kW)	U (%)	UCS (MPa)	BTS (MPa)	Quartz Content (%)	CLI	Spacing (cm)	RQD (%)	Basic RMR	Q-system	GSI	ROP (mm/rev)
4150	450	19,93	30	5,4	5	90	0,1	10	34,49	0,22	15	15,11
3030	390	22,92	30	5,4	15	80	0,1	10	34,49	0,17	15	9,81
4180	520	26,46	60	6,9	5	90	0,2	40	47,42	1,67	35	7,47
4030	600	25,76	40	6	5	90	0,15	25	42,93	0,83	20	10,83
4430	700	29,72	50	6,5	20	75	0,15	30	44,53	1,25	35	8,96
4430	650	24,79	65	7,1	5	90	0,1	15	45,14	0,75	20	10,15
4380	770	30,90	55	6,7	5	90	0,15	30	46,95	1,88	35	8,66
4450	700	35,42	70	7,3	5	90	0,1	15	45,53	0,75	20	7,97
4576	611	26,39	60	6,9	20	75	0,15	30	42,36	1,88	35	9,75
4194	669	29,17	70	7,3	20	75	0,15	30	36,15	0,83	25	8,09
4009	795	17,71	60	6,9	15	80	0,2	40	47,42	5,00	40	13,16
4428	542	22,92	50	6,5	5	90	0,1	15	38,91	0,75	20	15,98
4653	589	15,97	60	6,9	15	80	0,2	50	39,09	1,39	30	13,88
4081	558	18,40	50	6,5	5	90	0,2	50	48,27	8,33	45	11,52
4478	616	26,39	55	6,7	5	90	0,2	45	47,83	7,50	45	12,39
5103	739	27,08	60	6,9	15	80	0,25	60	48,38	6,67	50	11,86
4489	668	37,85	55	6,7	5	90	0,25	50	46,18	5,56	50	11,96
5037	751	26,04	65	7,1	5	90	0,25	60	48,78	6,67	50	11,24
5379	722	29,86	100	8,2	30	50	0,3	75	54,71	12,50	55	10,38
6289	822	19,79	130	9	30	50	0,3	75	61,47	12,50	60	9,82

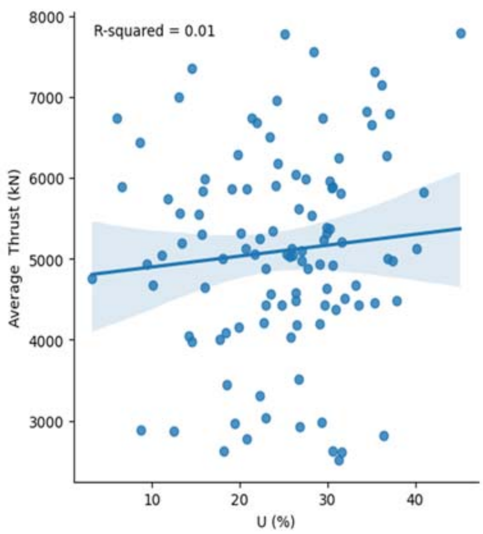
3.5 RESULTS AND DISCUSSIONS

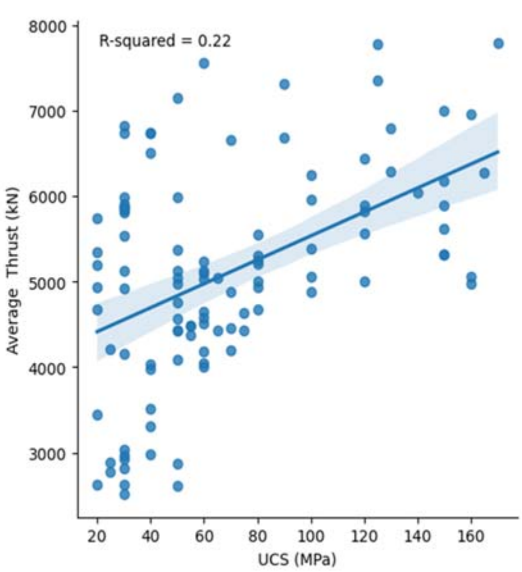
A statistical analysis was conducted to compare rock properties from a generated database with field data on rock cutting forces obtained from a TBM (Tunnel Boring Machine) in the Iranian tunnels project. Regression equations were developed based on the analysis, and the statistical parameter R^2 (determination coefficient) was evaluated using a Python program.

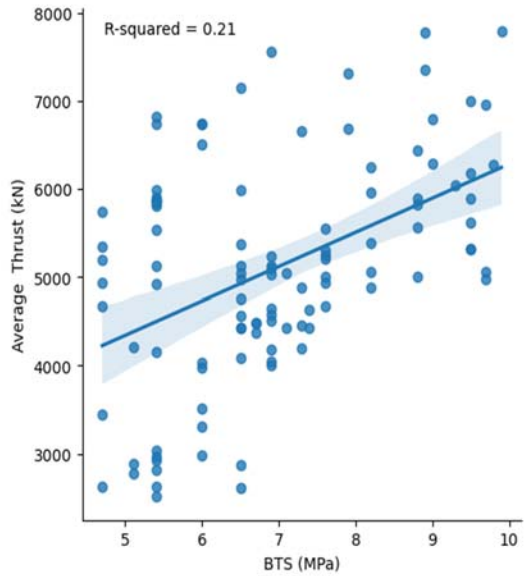
The Python platform is utilized to analyze the cutting force dataset as described earlier. Initially, a simple linear regression model is employed to measure the correlation between the cutting force and each influencing parameter individually. Subsequently, a multilinear regression model is implemented to investigate the combined effects of multiple parameters. Additionally, various nonlinear models are explored. The dependent variable in these analyses is the rock cutting force, while the independent variables include Power, Utilization factor, UCS, BTS, Quartz Content, CLI, fracture spacing, RQD, Basic RMR, Q-system, and GSI.

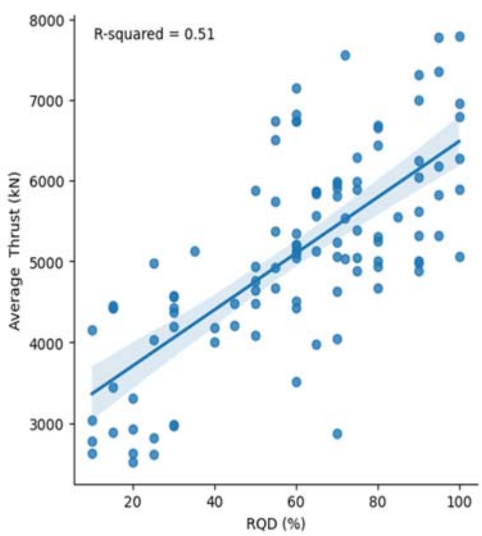
Figure 20 illustrates the linear correlation between cutting force and other parameters. According to scatter plots we can see that the best correlation is between Cutting force and RQD. It can be assumed that quality of rock may has more influence on cutting force than other parameters. But as we know all factors affect simultaneously.

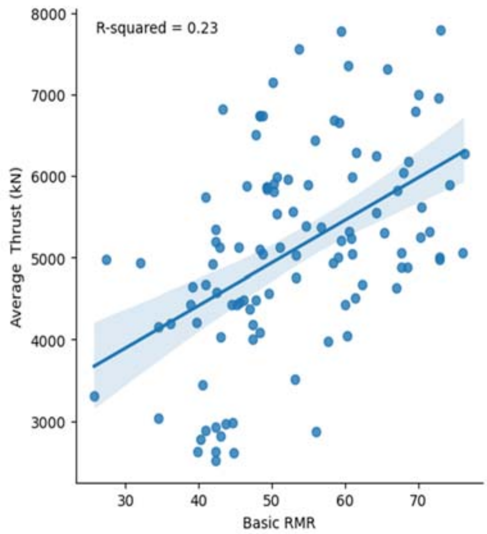


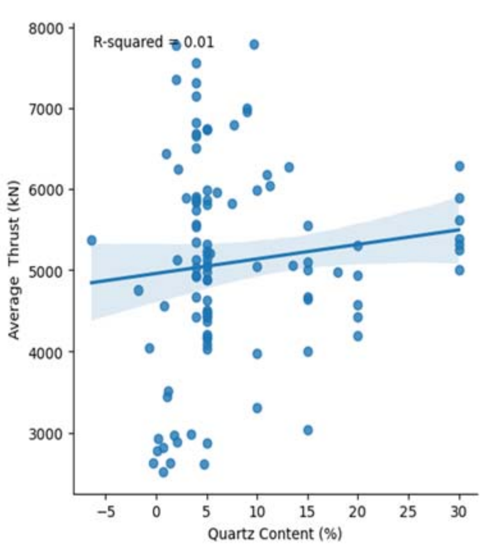


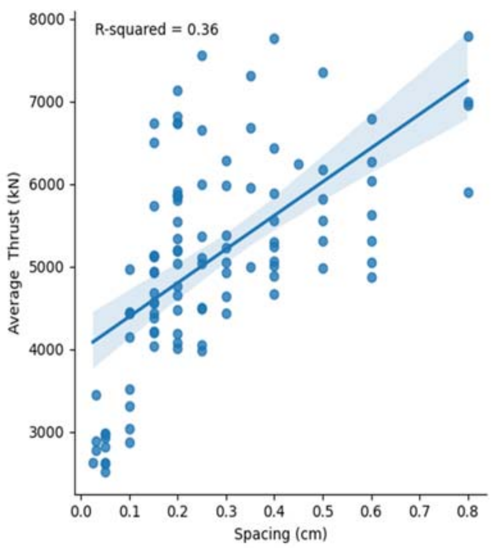

R-squared = 0.22
Average Thrust (kN)
UCS (MPa)


R-squared = 0.21
Average Thrust (kN)
BTS (MPa)


R-squared = 0.51
Average Thrust (kN)
RQD (%)


R-squared = 0.23
Average Thrust (kN)
Basic RMR


R-squared = 0.01
Average Thrust (kN)
Quartz Content (%)


R-squared = 0.36
Average Thrust (kN)
Spacing (cm)

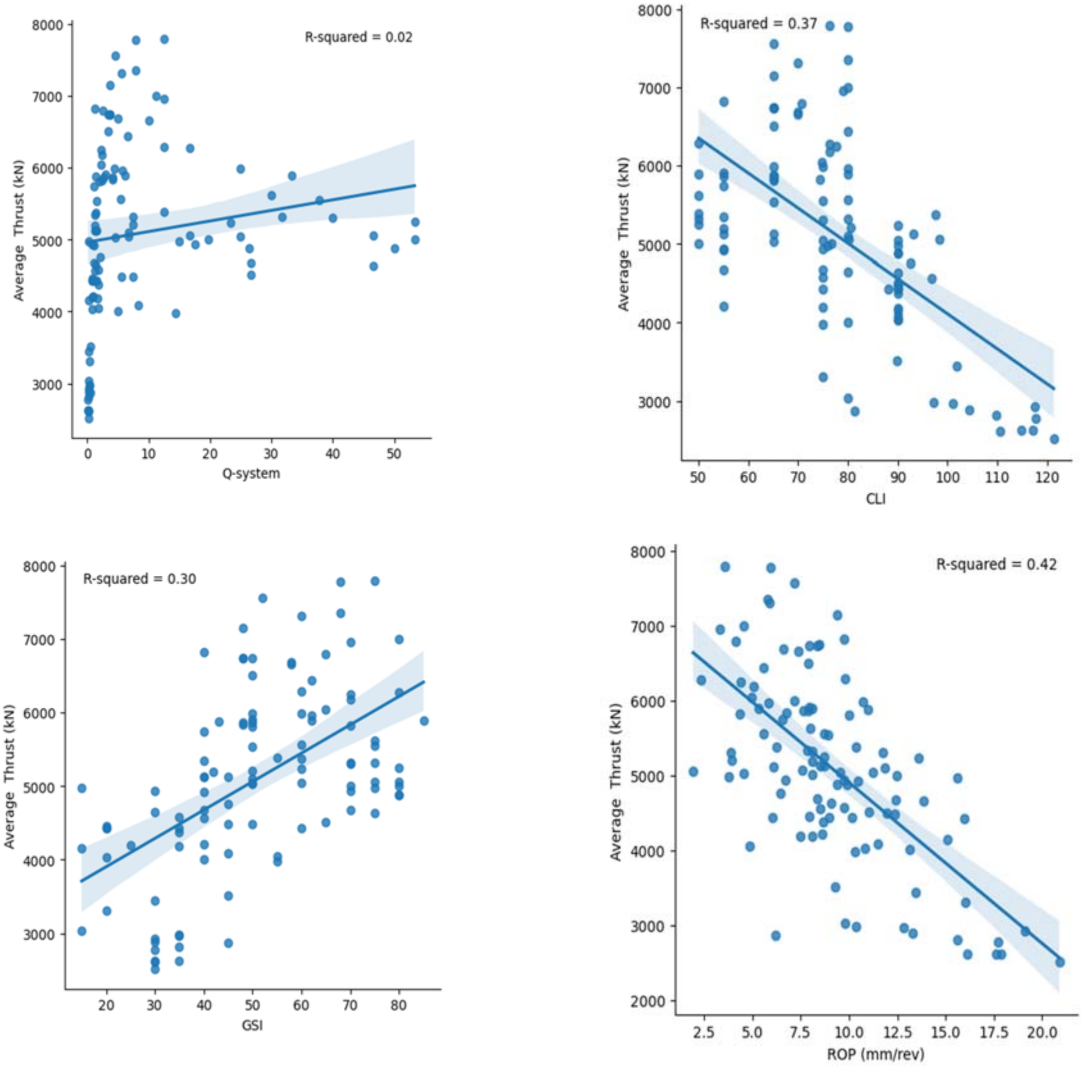


Figure 20. Scatter diagram between cutting force and other parameters of Iranian tunnels.

A correlation matrix is a tabular representation that shows the correlation coefficients between pairs of variables in a dataset. Each cell in the matrix displays the correlation coefficient between two variables, which measures the strength and direction of the linear relationship between them. It also shows high correlation coefficient between RQD and cutting force (Figure 21).

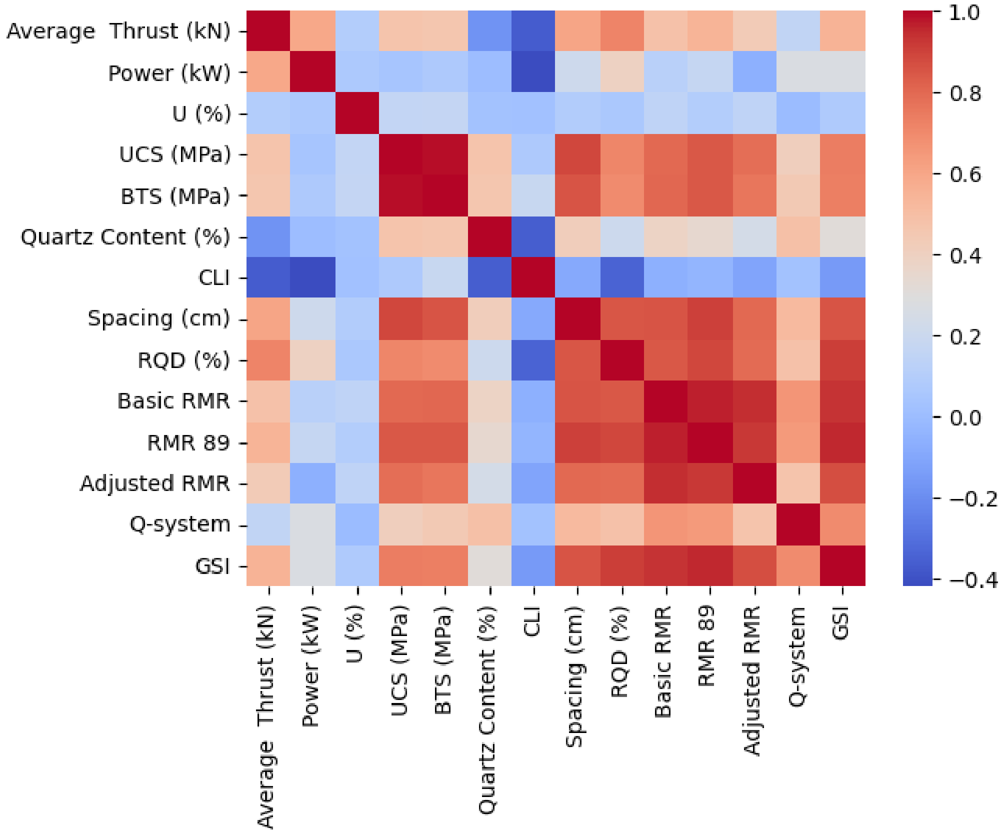


Figure 21. Correlation matrix of Iranian tunnels.

As evident from the correlation matrix (Figure 21), the input parameter with the greatest influence is the Rock Quality Designation (RQD). This finding is logical because, as mentioned in section 2.3.1, RQD is a crucial parameter in assessing the quality of rock mass, which can significantly impact the penetration rate of a Tunnel Boring Machine (TBM). This is because RQD is used to evaluate the extent of fractures in the rock, which becomes particularly relevant when the TBM is excavating through hard rock formations. During excavation, the TBM exerts substantial force on high-quality rock to break it and create a tunnel. As the TBM progresses, it encounters different types of rocks with varying strengths and properties. When encountering high-quality rock with a high RQD value, the TBM may require more cutting force and energy to break through the rock, potentially slowing down the penetration rate of the TBM.

Based on the correlation findings, it was determined that spacing had the least influence among the parameters studied. The spacing between rock joints can indeed affect the strength and brittleness of the rock. However, in certain situations, the rock may be strong enough to withstand the impact of the TBM, and the joint spacing may not significantly affect the cutting force.

Additionally, ground support measures can be implemented to stabilize the rock mass surrounding the tunnel, reducing the impact of joint spacing on the penetration rate of the TBM.

Based on the analysis of simple correlation results, it is concluded that linear regression analysis may not be a suitable approach to achieve the objectives of this study. Therefore, in order to enhance the correlations between rock mass properties and rock cutting force, multiple regression analysis, including both linear and non-linear methods, will be explored.

According to the analysis we received the formulas for cutting force prediction (see Table 8). With the help of such formulas, we can predict the cutting force, which directly affects the rate of penetration. These and other interrelated factors form the basis for drilling planning.

Table 10. Prediction formula based on regression analysis.

Multilinear regression analysis	$F_n = 4947.99 + 2.05 \times Power(kW) + 3.05 \times U(\%) - 0.08 \times UCS(MPa) + 301.33 \times BTS(MPa) - 79.54 \times Quartz\ Content(\%) - 42.69 \times CLI + 2378.44 \times Spacing(cm) - 5.40 \times RQD(\%) + 1.26 \times Basic\ RMR - 11.85 \times Q - system + 7.17 \times GSI$	$R^2 = 0.63$
Non-linear regression analysis	$F_n = 39.91 \times Power(kW)^{0.68} + 0.00 \times U(\%)^{12.62} + 0.00 \times UCS(MPa)^{3.40} + 3.77 \times BTS(MPa)^{0.74} + 6.53 \times Quartz\ Content(\%)^{-0.79} + 19.58 \times CLI^{0.74} + 0.81 \times Spacing(cm)^{0.76} + 19.41 \times RQD(\%)^{1.01} + 3.05 \times Basic\ RMR^{0.29} + 5.17 \times Q - system^{-0.33} + 2.48 \times GSI^{0.03} + 2.41$	$R^2 = 0.19$

It is found that rock cutting force could be estimated as a function of several rock properties and depth of cut using the equations obtained from this study. Based on the non-linear prediction equation Utilization factor and UCS don't affect the rock cutting force.

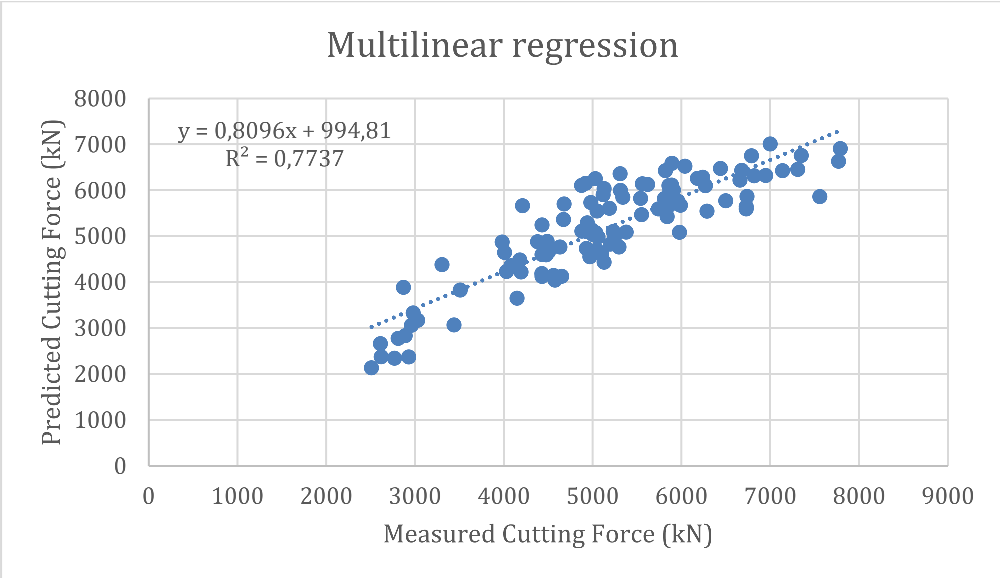


Figure 22. Relations between measured Fn and predicted Fn based on Iranian tunnels data.

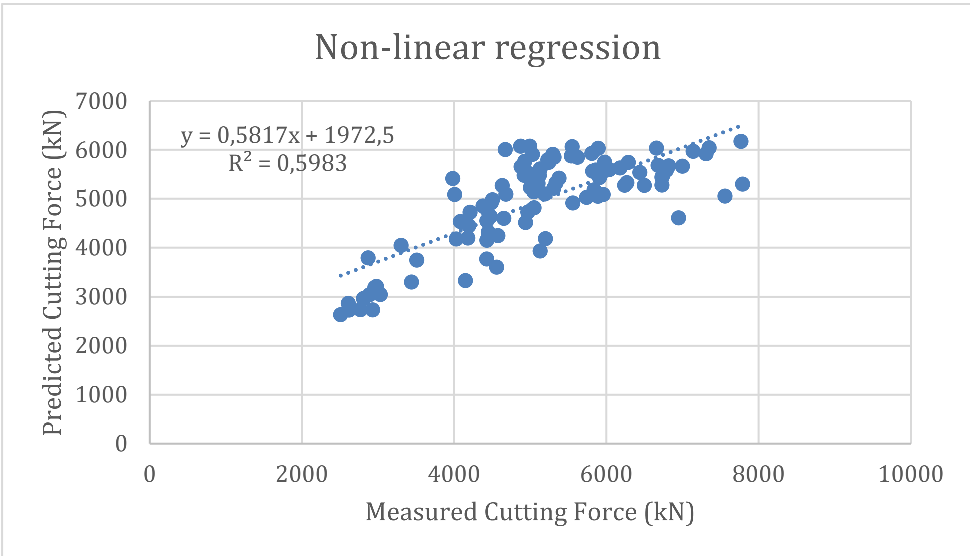


Figure 23. Relations between measured Fn and predicted Fn based on Iranian tunnels data.

As a result, the estimated cutting force is compared with actual measured cutting force as shown in Figures 22-23, where the coefficient of determination (R^2) is equal to 0.77 for Multilinear regression and 0.63 for Non-linear regression, which means that the equations is useful and reliable to assess cutting force performance. It should be mentioned that non-linear equations are more reliable than linear models since the cutting force of rocks shows non-linear relationships with rock properties and cutting force in real case situations.

4. CONCLUSIONS AND RECOMMENDATIONS

4.1 CONCLUSIONS

The primary objective of this thesis was to investigate the impact of rock properties on the rock cutting force of Tunnel Boring Machine (TBM). To achieve this, a comprehensive literature review was conducted to critically evaluate excavation methods, TBM machine parameters, and qualities of intact rock. This review provided a critical understanding of the current state of knowledge in the field, which formed the basis for further research. A database was compiled using actual measurements of TBM rock cutting force, machine parameters (Power and Utilization factor), and rock properties, including Uniaxial Compressive Strength, Brazilian Tensile Strength, Quartz Content, Cutter Life Index, Rock Quality Designation, Rock Mass Rating, Q-system, Fracture Spacing, and Geological Strength Index. The data was collected from three Iranian tunnel projects, namely Karaj, Chomrood, and Zagros water conveyance tunnels.

Raw database information was collected from literature sources on TBM tunnel excavations in Iranian tunnel projects. This data was used to support the development of a cutting force estimation model and allowed for the identification of key input parameters.

Different types of regression analyses, including linear and non-linear multiple regressions, were tested on a dataset collected from existing literature to determine the most accurate method for estimating cutting force. Solely relying on simple linear regression is unrealistic, as the relationship between variables is complex. Equations developed from multilinear and non-linear regression analyses are reliable for assessing cutting force performance. Notably, non-linear equations are more dependable as cutting force in real-world scenarios exhibits non-linear relationships with rock properties. Based on the non-linear prediction equation, it can be concluded that the utilization factor and UCS (uniaxial compressive strength) do not significantly affect rock cutting force.

Based on the findings, it has been deduced that the essential factors for accurate prediction of tunnel boring machine (TBM) performance are intact rock and rock mass properties. In addition, it can be inferred that the interdependencies among various rock parameters and their potential influence on other machine parameters can collectively impact the cutting force, resulting in fluctuations in the cutting force magnitude.

4.2 RECOMMENDATIONS

In order to enhance the findings of this study, future research could consider expanding the dataset to improve the accuracy and precision of the prediction equations. This enlarged dataset could also be utilized to develop more sophisticated models that incorporate advanced techniques such as machine learning, artificial intelligence, and swarm optimizations. Additionally, further analysis and testing should be conducted to validate the reliability and accuracy of the prediction equations. This could involve employing alternative statistical methods, conducting sensitivity analyses, or testing the equations on new, independent datasets. Furthermore, collaboration with experts from diverse fields such as computer science or engineering may yield innovative solutions for improving the prediction models. An interdisciplinary approach could lead to more precise and effective predictions with practical applications in the real world. It should also be noted that the limitation of this work lies in not taking into account such categorical data as faults, layering and depth direction, which affect the cutting force.

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6. APPENDICES

APPENDIX 1 - IRANIAN TUNNELS PROJECT DATABASE

Average Thrust (kN)	Power (kW)	U (%)	UCS (MPa)	BTS (MPa)	Quartz Content (%)	CLI	Spacing (cm)	RQD (%)	Basic RMR	Q-system	GSI	ROP (mm/rev)
4150	450	19,93	30	5,4	5	90	0,1	10	34,49	0,22	15	15,11
3030	390	22,92	30	5,4	15	80	0,1	10	34,49	0,17	15	9,81
4180	520	26,46	60	6,9	5	90	0,2	40	47,42	1,67	35	7,47
4030	600	25,76	40	6	5	90	0,15	25	42,93	0,83	20	10,83
4430	700	29,72	50	6,5	20	75	0,15	30	44,53	1,25	35	8,96
4430	650	24,79	65	7,1	5	90	0,1	15	45,14	0,75	20	10,15
4380	770	30,90	55	6,7	5	90	0,15	30	46,95	1,88	35	8,66
4450	700	35,42	70	7,3	5	90	0,1	15	45,53	0,75	20	7,97
4576	611	26,39	60	6,9	20	75	0,15	30	42,36	1,88	35	9,75
4194	669	29,17	70	7,3	20	75	0,15	30	36,15	0,83	25	8,09
4009	795	17,71	60	6,9	15	80	0,2	40	47,42	5,00	40	13,16
4428	542	22,92	50	6,5	5	90	0,1	15	38,91	0,75	20	15,98
4653	589	15,97	60	6,9	15	80	0,2	50	39,09	1,39	30	13,88
4081	558	18,40	50	6,5	5	90	0,2	50	48,27	8,33	45	11,52
4478	616	26,39	55	6,7	5	90	0,2	45	47,83	7,50	45	12,39
5103	739	27,08	60	6,9	15	80	0,25	60	48,38	6,67	50	11,86
4489	668	37,85	55	6,7	5	90	0,25	50	46,18	5,56	50	11,96
5037	751	26,04	65	7,1	5	90	0,25	60	48,78	6,67	50	11,24

5379	722	29,86	100	8,2	30	50	0,3	75	54,71	12,50	55	10,38
6289	822	19,79	130	9	30	50	0,3	75	61,47	12,50	60	9,82
4969	762	27,08333	50	6,5	5	90	0,1	25	27,28535	0,183333	15	15,59
5232	811	29,51389	60	6,9	5	90	0,3	70	60,78566	23,33333	60	13,59
5297	803	15,625	80	7,6	20	75	0,4	80	65,30172	40	70	11,78
5062	707	25,34722	100	8,2	5	98,4	0,4	70	67,64272	46,66667	75	7,59
4504	626	31,94444	60	6,9	5	90	0,25	60	61,38467	26,66667	65	11,02
5003	634	36,80556	120	8,8	30	50	0,4	80	72,89772	53,33333	80	8,12
4633	651	29,86111	75	7,4	5	90	0,3	70	66,95416	46,66667	75	9,10
5244	791	22,22222	80	7,6	30	50	0,4	80	70,30172	53,33333	80	8,73
4880	735	27,77778	70	7,3	5	90	0,4	75	68,51922	50	80	9,40
5621	758	26,73611	150	9,5	30	50	0,6	90	70,35614	30	75	7,99
5314	727	20,13889	150	9,5	30	50	0,6	95	71,47964	31,66667	75	8,11
5894	752	30,55556	150	9,5	30	50	0,8	100	74,26396	33,33333	85	8,09
4930	759	29,16667	80	7,6	20	75	0,3	80	58,36066	17,6	70	9,74
4875	769	22,91667	100	8,2	5	90	0,6	90	67,61114	26,4	80	9,88
4995	789	18,05556	80	7,6	15	76,6	0,35	90	58,99267	19,8	70	12,46
4672	834	10,06944	80	7,6	15	75	0,4	80	62,30172	26,66667	70	12,42
3304	612	22,22222	40	6	10	75	0,1	20	25,71285	0,44	20	16,02
5552	820	15,27778	80	7,6	15	75	0,5	85	64,27038	37,77778	75	8,69
5046	605	11,11111	50	6,5	10	75	0,3	75	60,96016	25	60	9,54
5979	785	15,97222	50	6,5	10	75	0,3	75	60,96016	25	60	10,73
3982	746	14,58333	40	6	10	75	0,25	65	57,63017	14,44444	55	10,32
5910	750	24,08333	30	5,4	4	55	0,2	70	50,2017	2,916667	50	7,96

5860	830	19,08333	30	5,4	5	55	0,2	65	49,2282	2,708333	50	7,88
6660	850	35	70	7,3	4	70	0,25	80	59,12767	10	58	7,37
4680	740	33,20833	20	4,7	4	55	0,15	55	40,92026	1,145833	40	8,36
4210	690	22,70833	25	5,1	5	55	0,15	45	39,66276	0,9375	40	8,64
5860	800	20,83333	30	5,4	4	65	0,2	65	49,2282	4,0625	48	7,62
6730	800	29,5	30	5,4	5	65	0,2	60	48,2847	3,75	48	7,95
6500	780	23,45833	40	6	4	65	0,15	55	47,77826	3,4375	50	7,87
6730	750	21,375	40	6	5	65	0,15	60	48,69176	3,75	50	8,34
5840	690	15,83333	30	5,4	4	65	0,2	65	49,2282	4,0625	48	6,74
5990	780	27,5	30	5,4	5	65	0,25	70	50,69467	4,375	50	7,16
5340	780	23,75	20	4,7	4	55	0,2	60	42,3357	1,25	40	7,82
5190	710	13,41667	20	4,7	5	55	0,2	60	42,3357	1,25	42	8,11
5120	780	40,20833	50	6,5	4	65	0,15	65	45,50426	1,354167	45	6,08
4940	600	9,375	20	4,7	4	55	0,15	50	32,03676	0,833333	30	6,72
5740	720	11,75	20	4,7	4	55	0,15	55	40,92026	1,145833	40	6,55
7310	750	35,33333	90	7,9	4	70	0,35	90	65,70167	5,625	60	5,87
6680	740	21,95833	90	7,9	4	70	0,35	80	58,54467	5	58	6,61
6820	890	34,5	30	5,4	4	55	0,2	60	43,2847	1,25	40	9,76
7140	970	36,125	50	6,5	4	65	0,2	60	50,0627	3,75	48	9,38
6740	840	6,041667	40	6	5	65	0,2	55	48,2802	3,4375	48	8,45
4920	860	30,625	30	5,4	4	55	0,15	55	41,86926	1,145833	40	10,48
5130	870	20,70833	30	5,4	5	55	0,15	60	42,78276	1,25	40	8,70
5540	860	28,25	30	5,4	4	65	0,2	72	50,5995	1,5	50	8,94
5810	890	31,54167	30	5,4	5	65	0,2	70	50,2017	1,944444	50	9,99

5870	910	30,5	30	5,4	4	65	0,2	50	46,4877	1,388889	43	10,97
6440	680	8,666667	120	8,8	1	80	0,4	80	55,89772	6,6	62	5,60
7350	740	14,58333	125	8,9	2	80	0,5	95	60,36288	7,8375	68	5,80
7770	780	25,08333	125	8,9	2	80	0,4	95	59,45772	7,8375	68	5,93
5890	570	6,541667	120	8,8	3	80	0,4	75	54,86422	6,1875	62	5,32
5560	590	13,20833	120	8,8	4	80	0,4	65	52,88722	5,3625	60	5,59
5310	530	29,875	150	9,5	5	80	0,5	90	60,48688	7,425	70	3,88
5960	610	30,20833	100	8,2	6	80	0,35	70	52,17667	5,775	62	5,82
5030	870	25,70833	60	6,9	4	65	0,2	72	53,2065	4,5	50	4,56
7560	610	28,45833	60	6,9	4	65	0,25	72	53,69947	4,5	52	7,17
4560	408	23,54167	50	6,5			0,15	30	49,52976	1,25	40	8,51
5130	472	25,95833	60	6,9			0,15	35	51,12226	1,458333	40	8,54
5200	421	31,58333	80	7,6			0,2	60	59,4297	7,5	50	3,92
4760	250	3,166667	50	6,5			0,2	50	53,2657	2,083333	45	6,47
6950	325	24,16667	160	9,7			0,8	100	72,69296	12,5	70	3,31
7790	502	45,125	170	9,9			0,8	100	73,08196	12,5	75	3,58
7000	659	13	150	9,5			0,8	90	69,98696	11,25	80	4,53
6790	588	37,08333	130	9			0,6	100	69,65514	2,5	65	4,16
6180	623	24,29167	150	9,5			0,5	95	68,61038	2,375	70	5,07
6040	646	26,33333	140	9,3			0,6	90	67,88714	2,25	65	4,96
5820	607	40,91667	120	8,8			0,5	95	67,08338	2,375	70	4,37
6240	550	31,33333	100	8,2			0,45	90	64,29378	2,25	70	4,38
4430	571	33,54167	75	7,4			0,3	60	60,03716	1,5	60	6,05
5370	339	30,20833	50	6,5			0,25	55	56,64217	1,375	60	6,27

3510	303	26,66667	40	6			0,1	60	53,18085	0,5	45	9,27
2870	277	12,5	50	6,5			0,1	70	55,96685	0,583333	45	6,22
4050	210	14,16667	60	6,9			0,25	70	60,30167	1,75	55	4,85
2980	314	29,29167	40	6			0,05	30	44,62996	0,333333	35	10,39
2810	267	36,375	30	5,4			0,05	25	42,98746	0,277778	35	15,61
2960	304	19,375	30	5,4			0,05	30	43,72096	0,333333	35	12,83
2610	246	31,58333	50	6,5			0,05	25	44,76546	0,277778	30	16,12
4980	621	37,41667	160	9,7			0,5	90	72,91588	15	75	3,78
6270	510	36,75	165	9,8			0,6	100	76,26164	16,66667	80	2,33
5050	373	21,75	160	9,7			0,6	100	76,06214	16,66667	80	1,94
2620	234	18,125	30	5,4			0,05	20	42,28396	0,222222	30	17,87
2510	208	31,33333	30	5,4			0,05	20	42,28396	0,222222	30	20,89
2930	229	26,79167	30	5,4			0,05	20	42,28396	0,222222	30	19,13
2620	337	30,54167	20	4,7			0,025	10	39,75465	0,111111	35	17,63
2770	266	20,83333	25	5,1			0,03	10	40,28699	0,111111	30	17,72
3440	403	18,54167	20	4,7			0,03	15	40,45099	0,166667	30	13,46
2890	337	8,75	25	5,1			0,03	15	40,93049	0,166667	30	13,29