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# A model for estimating the penetration of hard rock tunnel boring machine in practice

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## Abstract

Assessing the rate of penetration (ROP) of Tunnel Boring Machine (TBM) is one of the most crucial tasks in rock excavation and bore-ability, since the ROP is a main essential input parameter in the scheduling and execution of mechanized tunnelling projects. Despite the advances in tunnelling, a reliable estimate of the ROP is still posing challenges. Hence, this research aims to develop a model to estimate TBM penetration rate in hard rocks based on intact rock, rock mass properties and also machine specifications. In this study, 557 resulting datasets gathered from different tunnelling projects were utilized to predict the ROP using simple linear, linear multiple regression (LMR), and non-linear multiple regression (NLMR) analysis techniques. Firstly, rock fracture index (FI) is introduced as input and then the variety of multiple variable regressions were performed using the statistical software. It is found that the estimation of TBM penetration depend on both intact rock strength and discontinuity properties in rock mass and TBM operational parameters. As a result, nonlinear multiple variable regression equations were developed, and the best-performingmodel, with a correlation coefficient of 0.82, is introduced for TBM tunnelling in practice.

## Keywords

Fracture Index, Hard Rock Mass, Penetration Rate, Tunnel Boring Machine, Tunnelling.

## 1 Introduction

Mechanized excavation refers to the method of rock breakage where the rock is entirely removed from the excavation face by the action of mechanical boring/cutting tools. Mechanized rock excavation is traditionally compared to drill and blast operation. The characteristic advantages of mechanical excavation are increased safety, higher production rate, less labour-intensive operation, higher degree of automation, minimum damage to the walls, better control over the process, uniformity of product size, elimination of blast vibrations, and better ventilation in underground openings. The most common types of mechanized excavators are tunnel boring machines (TBMs), roadheader, raise boring machine (RBM), continuous miner, and longwall drum shear to be used for either civil or mining construction.

One of the important indices or parameters used to evaluate the performance of TBM is the rate of penetration (ROP). The ROP is defined as the ratio of excavation distance to the operating time for the duration of the tunnel construction process. Many parameters are known to influence the ROP during tunnelling which include intact rock properties, rock mass properties and the machine specifications (Rostami and Ozdemir 1993; Bruland 1998; Kim 2004; Alber 2008; Delicia et al. 2013; Hassanpour et al. 2024; Yagiz et al. 2024; Olaiya et al. 2026) as summarized in Table 1.Besides properties of intact rock and rock mass features, in-situ stress distribution around the underground opening is also critical for excavation process, especially unstable ground condition encountered (Adoko et al., 2020).

Table 1.Common parameters influencing the penetration rate of TBM.

| **Intact rock parameters** | **Rock mass parameters** | **Machine parameters** |
|---|---|---|
| Uniaxial compressive strength | Rock mass fabric | Total thrust ($F_t$) |
| Point load Index | Rock texture | Normal force ($F_n$) |
| Brazilian tensile strength | Orientation of discontinuities | Cutter diameter |
| Rock brittleness, Toughness | Spacing between the fractures | Cutter tip width, RPM |
| Hardness | Rock Quality Designation | Space between Cutters |
| Drilling rate index (DRI) | Fissures | Number of Cutters |
| Thin section analysis | Grain size and minerals | Cutterhead Power |

Accurate estimation of TBM penetration is of crucial significance for the successful completion of the mechanized excavation projects. It mainly includes the determination of the rock cutting force and efficiency under different cutter penetration depth and the determination of the optimum rock boring/cutting condition as well as tool consumption; however, this thesis focusses on the aspect of penetration prediction for hard rock tunnel boring machines.

From past to present, many TBM performance estimation models are introduced (Graham and Farmer 1976; Cassinelli et al. 1980; Huges, 1986; Innaurato et al. 1991; Rostami and Ozdemir 1993; Bruland 1998; Barton 2000; Yagiz 2002, 2008; Hassanpour 2011; Goodarzi et al. 2021; Pourhashemi et al. 2021; Yang, et al., 2022; Yazitova et al. 2025). Most commonly used and known models for estimating the TBM penetration is summarized herein. Table 2 provides an overview of various empirical models that have been adopted for practical applications. These models have evolved from simpler to more sophisticated forms. Most complex but accurate models incorporate the key parameters affecting penetration rate, such as intact rock properties, rock mass characteristics, and machine parameters as input. In table 2, the most common empirical models and equations are introduced herein to give an idea for the readers who is familiar with TBM project practice.The purpose of this study is to development of the model for predicting TBM penetration in hard rocks based on intact rock, rock mass properties, and machine specifications, all of which have an influence on TBM tunnelling.

# 2 Projects

In this study, a database was developed using data from six different tunnel projects, including Queens Water Tunnel in the USA, Manapouri hydropower tunnel in New Zealand, Miryang Dam Tunnel in South Korea, and three Iranian Water Conveyance Tunnels (Karaj, Zagros, and Ghomrood).

The Queens Water Tunnel, 7.5 km long and 7 m in diameter, was excavated in complex geological formations beneath Brooklyn and Queens using a high-power TBM. The tunnel's geology consists of metamorphosed igneous rocks including gneiss to ortho gneiss, pegmatite with shear zones and faults (Queens Tunnel Project Report 2000; Yagiz 2002).

The Manapouri Second Tailrace Tunnel in New Zealand, part of a major hydroelectric project, faced challenging conditions due to the region's complex geology, including hard and abrasive rocks like

met-andesite and gneiss. A 2 km section of the tunnel, 10 m in diameter, was analysed for this study (Manapouri Report 2001; Yagiz et al. 2024a).

The Miryang Dam Tunnel in South Korea, 7.6 km long with a 2.6 m diameter, was constructed using both Drill-Blast and TBM methods. The tunnel faced challenges due to high compressive strength and abrasive granite (Kim 2004; Yagiz et al., 2010).

Data from the Karaj, Zagros, and Ghomrood water conveyance tunnels in Iran, excavated through various geological zones with sedimentary, metamorphic, volcanic, and pyroclastic rocks, were also included in the database (Hassanpour et al. 2024; Yagiz et al. 2024a, b).

Table2. Summary of common empirical models for estimating of the TBM penetration rate.

| References | Equations | Outputs |
|---|---|---|
| Grahan (1976) | $P_{rev} = 3940 \cdot F_n/\sigma_c$ | $P_{rev}$ |
| Farmer and Glossop (1980) | $P_{rev} = 624 \cdot F_n/\sigma_c$ | $P_{rev}$ |
| Cassinelli et al. (1982) | $ROP = -0.0059RSR + 1.59$ | PR |
| Hughes (1986) | $ROP = 1.667 \cdot (F_n/\sigma_c)^{1.2} \cdot (2/d)^{0.6}$ | PR |
| Innaurato etal. (1991) | $ROP = {\sigma_c}^{-0.437} - 0.047 \cdot RSR + 3.15$ | PR |
| Rostami &Ozdemir (1993) | $ROP = (F_n, \sigma_c, \sigma_t, rpm, s, T, R, \emptyset)$ | PR |
| Yagiz (2002) | $ROP = (F_n, \sigma_c, \sigma_t, rpm, s, T, R, \emptyset, BI, \alpha, DPW)$ | PR |
| Gehring (1995) | $ROP = 4 \cdot \frac{F_n}{\sigma_c}$ | $P_{rev}$ |
| NTNU (Bruland 1998) | $ROP = (f_n, \sigma_c, J_c, RPM, S, d, q, \alpha)$ | PR |
| $Q_{TBM}$ (Barton 1999) | $ROP = 5 \cdot {Q_{TBM}}^{-0.2}$; $Q_{TBM} = 5Q \cdot \gamma \cdot \sqrt[3]{Q \cdot \sigma_c/100/F_n}$ | PR |
| Bieniawski et al. (2007) | $ARA_T = 0.324 \cdot RME - 6.8$ If UCS $\leq$ 45 MPa<br>$ARA_T = 0.839 \cdot RME - 40.8$ If UCS $>$ 45 MPa | AR |
| Yagiz (2008) | $ROP = 1.039 + 0.028 \cdot BI - 0.003 \cdot \sigma_c + 0.437 \cdot \log(a) - 0.219 \cdot DPW$ | PR |
| Hassanpour et al. (2011) | $FPI = Exp(0.008 \cdot UCS + 0.015 \cdot RQD + 1.384)$ | FPI |
| Goodarzi et.al. (2021) | $ROP = \exp(0.006F_n - 0.016\sigma_c + 1.833)$ | PR |
| Pourhashemi et al. (2021) | $P_{rev} = 1.98 + 0.035F_n - 0.03\sigma_c - 0.011GSI$ | $P_{rev}$ |
| Xu etal. (2021) | $P_{rev} = 16.888 - 0.025\sigma_c - 108243K_v$ | $P_{rev}$ |
| Yazitova et al. (2025) | $ROP = \frac{F_n^{0.308} \cdot WFI^{0.136} \cdot RPM^{-0.027} \cdot CHD^{2.875}}{8.211 \cdot UCS^{0.101} \cdot e^{0.583 \cdot CHD}}$ | ROP |

**Note:** ROP, penetration rate (m/h); Prev, penetration per revolution (mm/rev); RPM, cutterhead rotation speed (rev/min); Fn, cutter normal force (kN/c); $\sigma_c$, uniaxial compressive strength (MPa); σt, Brazilian tensile strength (MPa); BI, brittleness index; D, tunnel diameter (m); d, cutter radius or diameter (m); s, cutter spacing (m); q, quartz content; RQD, rock quality designation; RSR, rock structure rating; QTBM, rock mass quality rating for TBM driven tunnels; GSI, geological strength index; α, the angle between the tunnel axis and the joint plane; Jc, RMR joint condition partial rating; Jv, volumetric joint count; DPW, distance between the plane of weakness; q, quartz content; Kv, the intactness index of rock mass.

# 3 Datasets

The dataset includes intact rock properties (such as uniaxial compressive strength), rock mass properties like frequency of fracture spacing, machine specifications (e.g., disc cutter load), and TBM performance data (penetration rate) compiled from six different projects having different operational

parameters. Each input variable, such as rock strength, discontinuities, and machine output, was carefully examined and quantified to create a comprehensive database with 557 datapoints. The statistical range and data distribution were analysed using histograms to ensure the dataset's suitability for developing and testing empirical models as given in Table 3.

Table 3.Statistical description of the dataset in the database.

| **Parameters** | **# of data** | **Minimum** | **Maximum** | **Mean** | **Std. dev** |
|---|---|---|---|---|---|
| UCS (MPa) | 557 | 20.0 | 300.0 | 155.8 | 61.6 |
| WFI | 557 | 0.1 | 189.9 | 17.05 | 33.0 |
| $F_n$ (kN) | 557 | 61.4 | 294.6 | 193.6 | 65.5 |
| CHD (m) | 557 | 2.6 | 10.1 | 6.4 | 2.3 |
| RPM (mm/rev) | 557 | 5.1 | 10.7 | 7.9 | 1.7 |
| ROP (m/h) | 557 | 0.2 | 4.8 | 1.8 | 0.8 |

**Note:** UCS, uniaxial compressive strength of rock (MPa); WFI, weighted fracture index; Fn, cutter load; CHD, cutter head diameter (m); RPM, rotational speed.

# 4 Model Development

In data science and engineering, a key step before developing predictive models is data partitioning. Typically, 80% of the data is used for training and 20% for testing, which provides a balance between a large training set for the model and a sufficient testing set to evaluate its performance. Consequently, developed dataset with 557 data point is divided into 445 training and 112 testing data. After examining the relationship between input variables using simple relations, linear multiple regression and non-linear multiple regression models are developed.

In order to find the best model, numerous linear multiple regression (LMR) and non-linear multiple regression (NLMR) were developed with different alternative input parameters including intact rock, rock mass properties as well as machine specification. Based on developed models utilizing variety of regression model techniques, the most accurate output is obtained and given in Equation 1 as follow:

$$\mathrm{ROP} = \frac{F_n^{0.308} \cdot \mathrm{WFI}^{0.136} \cdot \mathrm{RPM}^{-0.027} \cdot \mathrm{CHD}^{2.875}}{8.211 \cdot \mathrm{UCS}^{0.101} \cdot e^{0.583 \cdot \mathrm{CHD}}}, \qquad r = 0.82 \qquad (1)$$

It is found that the NLMR is superior to LMR in terms of correlation coefficients. It is also known that the nature and rock mass conditions inthe field are not homogeneous or isotropic; therefore, the relationships between the input variables and the ROP are not simple. As a result, the relationship between actual and predicted ROP is presented in Figure 1.To check the accuracy of the model, several statistical indices, such as coefficient of determination, root mean square error, mean absolute deviation, and variance account for ($R^2$, RMSE, MAD, VAF respectively) were obtained. Then, total ranking score method is used to find the best one among them to be introduced herein. Furthermore, the amount of error between measured and estimated ROP for each data point is presented in Figure 2 to show the variation of error along the excavation stations. The more information and model development process in this research could be found in Yazitova et al. (2025).

# 5 Conclusions

In this study, numerous LMR and NLMR models were developed using the established dataset. Accuracy of the models were checked using several alternative statistical indices, such as correlation coefficient, mean square error, root mean square error, and mean absolute percentage error. It was found that introduced nonlinear equation (Eq.1) is the most accurate among them, due to the quality

and number of input variables in the equation, as well as its performance based on statistical indices, particularly the correlation coefficient. Also, it is concluded that the NLMR is superior to LMR in terms of both input representation and output performance. As a result, the NLMR model equation introduced herein can be used, with caution, to estimate the ROP for scheduling purposes under similar rock and geological conditions. However, the application of the equation is limited to the range of dataset and the types of rocks considered in this study.

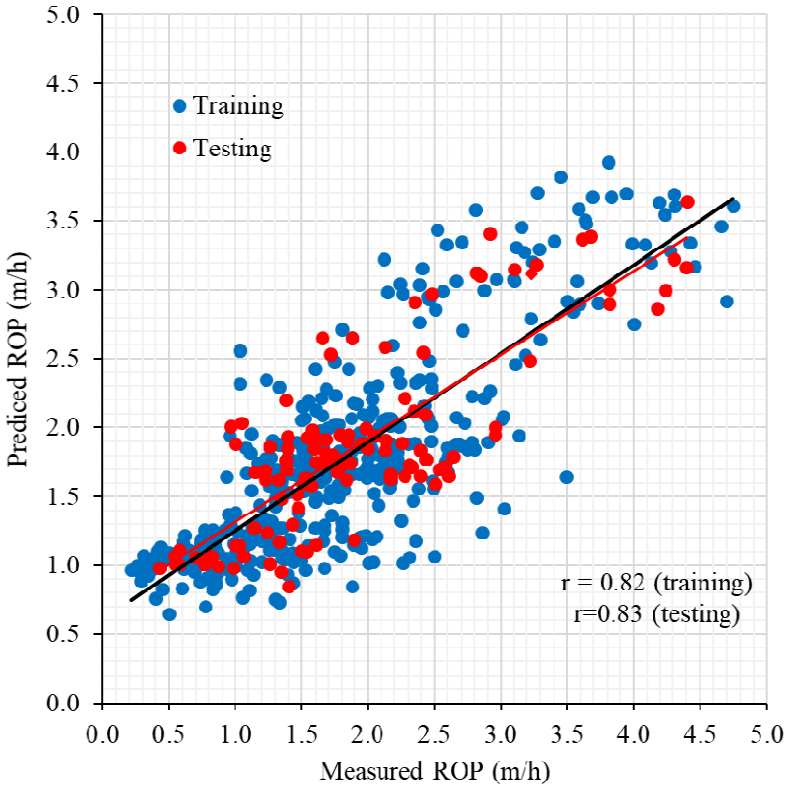



Fig.1 Relations of actual ROP with predicted ROP for both training and testing data.

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