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Oveis Farzay [1]*, Marilena Cardu [1], Seyedkhashayar Jamali[1]

1.Abstract

Predicting Open TBM performance in hard rock has been a long-standing challenge in tunneling engineering. The CSM and NTNU models have been widely used to estimate TBM advance rates and cutter forces based on rock mass properties and operational parameters. These models are detailed and widely applied, capable of predicting TBM performance with varying but acceptable accuracy, depending on the amount of input data available. However, they require comprehensive rock property investigations, which can be time-consuming and costly.

Data analysis of a global database from 105 tunneling projects revealed strong correlations between diameter and torque, power, and thrust. Building on these findings, the study combines linear regression and random forest models to deliver a fast, cost-effective tool for feasibility studies, performance checks, and optimizing TBM design and operation.

Monte Carlo simulations with 10,000 diameter samples defined the expected operational ranges for power, thrust, and torque. Sensitivity analysis further revealed that a 10% increase in diameter led to a 12.06% rise in power, a 13.80% increase in torque, but a 17.41% decrease in thrust. Conversely, a 10% reduction in diameter resulted in power decreasing by 17.66%, torque by 35.53%, and thrust by 26.04%, confirming torque as the most sensitive metric.

Keywords: OPEN TBM, Excavation Performance Metrics, Monte Carlo Simulation, Sensitivity Analysis

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2.Introduction

Tunneling in hard rock has improved greatly due to engineering progress. An important milestone was James S. Robbins's innovative work on tunnel boring machines (TBMs) starting in 1950 (Robbins) . Since then, continuous efforts have been made to evaluate critical parameters related to TBM design, performance, and maintenance. Howart (1994) studied TBM projects from 1974 to 1990 and built a database containing machine details, performance results, tunnel features, and ground conditions, showing how ground conditions strongly influence TBM performance. Highlighting the importance of ground conditions, Deere and Miller (1966) developed a report presenting a system to classify rocks based on their key properties, offering a standardized way to assess rock strength in engineering projects; likewise, Bieniawski (1973) introduced a method to classify jointed rock masses, aiding the selection of appropriate excavation and support techniques in different geological situations.

Building on these rock classification systems, Nelson (1983) introduced the Field Penetration Index (FPI) to predict TBM performance using rock mass features. Hassanpour, Rostami et al. (2009), (Hassanpour, Rostami et al. 2010, Hassanpour, Rostami et al. 2011) have developed practical models that relate FPI to RQD, UCS, and rock mass classification systems like RMR, Q, and GSI (Khatibi, Farzay et al. 2018, Khatibi, Ostadhassan et al. 2019, Shakouri, Farzay et al. 2019, Özçoban, Özfirat et al. 2022). Hamidi, Shahriar et al. (2010) applied RMR in a multiple linear regression model to estimate TBM performance in hard rock. Delisio and Zhao (2014) created a model for predicting TBM performance in blocky rock conditions using UCS and Volumetric Joint Count (JV). Similarly, Salimi, Faradonbeh et al. (2018) proposed empirical equations for TBM performance based on FPI derived from UCS, RMR and rock mass conditions.

Since rock classification alone does not fully explain TBM performance, the effectiveness of open TBM excavation significantly depends on machine efficiency, advancement speed, and tool wear (Wang, Gao et al. 2021). When open TBMs operate in hard rock conditions, drillability becomes a pivotal factor affecting performance. Yenice, Özdoğan et al. (2018) found Significant correlations between DRI and UCS, with Shore hardness being critical for predicting drillability. Yetkin, Özfırat et al. (2016) while examining the relation between rock mass cuttability index and rock drilling properties realize that Schmidt hardness is the most effective property for predicting DRI and RMCI values, providing a direct correlation between rock properties and cutting rates. Kahraman, Bilgin et al. (2003) reveals that UCS, BTS, and point load strength are dominant factors affecting penetration rate in percussive drilling.

To address these limitations, several modeling approaches have been proposed to better predict TBM performance, generally classified into four categories. The first category, which is called a single parameter, relies on data collected in the field during operation (Graham 1976, Farmer and Glossop 1980, Nelson 1983, Hughes 1986, Khatibi, Aghajanpour et al. 2018, Cardu, Todaro et al. 2024, Hamzaban, Rostami et al. 2025). Park, Lee et al. (2018), and (2021) applied the same principle and developed a database for statistical analysis of rock and machine parameters. Although these models are easy to use, they often do not accurately predict performance because they rely only on basic rock properties and ignore joint features. The second group includes Multiple Parameter Models like the Colorado School of Mines (CSM) model (Rostami and Ozdemir 1993, Rostami 1997, Cheema 1999), the Norwegian University of Science and Technology (NTNU) model (Bruland 1998) , and QTBM model (Barton 1999). These models consider both rock mass and machine parameters. The third group includes probabilistic models developed by Laughton (1998): These models use randomness and estimates to predict TBM performance, even when detailed information from similar tunnel projects is limited. The fourth category includes computer-based models created by Grima, Bruines et al. (2000), which use neural networks trained on large databases to improve predictions. However, these models usually have complicated structures and are difficult to understand (Grima and Babuška 1999, Grima, Bruines et al. 2000).

Among these approaches, the CSM and NTNU models are the two most common methods for predicting TBM performance. The CSM model mainly uses intact rock features, like uniaxial compressive strength, Brazilian tensile strength, and Cerchar Abrasivity Index. But since it depends mostly on these basic rock features, it is limited because it doesn't fully consider complexities like joints and fractures in rock masses (Farrokh, Rostami et al. 2012). To overcome this issue, changes have been made to include extra rock properties in the existing models (Grima and Babuška 1999, Grima, Bruines et al. 2000). Ramezanzadeh (2005) introduced adjustment factors to the CSM model to consider joints and rock discontinuities. The NTNU model, on the other hand, uses real-world data to predict TBM performance. It includes important rock features such as fracture frequency, fracture orientation, DRI, Bit Wear Index (BWI), Cutter Life Index (CLI), and rock porosity, among others (Yarali and Soyer 2013, Macias 2016, Özfırat, Yenice et al. 2016).

Although these established models are powerful, their reliance on extensive rock testing remains a significant drawback. While understanding rock properties is vital for predicting TBM performance, gathering this data requires a significant amount of time and cost. Although essential, this testing can be reduced by using TBM operational data from similar projects to simplify predictions and feasibility studies. Ates, Bilgin et al. (2014) statistically analyzed relationships between TBM diameter, thrust, and torque, validating results with real data from Turkish tunneling projects. Benato and Oreste (2015) proposed a practical new formula to estimate penetration per revolution using UCS, GSI, and thrust force. Cardu, Catanzaro et al. (2021) developed and statistically validated a comprehensive database compiled from numerous tunneling projects, establishing predictive models for TBM performance by analyzing correlations between key TBM operational parameters (e.g., excavation diameter, thrust, torque, cutterhead speed) and geological conditions. Yalei, Lijie et al. (2024) studied cutter head speed and found strong links between FPI, rock properties, and penetration rate. These user-friendly estimation models align closely with sustainability principles (Cardu, Farzay et al. 2023, Esmaeili, Hosseinzadeh et al. 2024, Hosseinzadeh, Haghighi et al. 2024), as their early-stage application facilitates the reduction of energy consumption, costs, and project duration, thereby enhancing overall efficiency and sustainability in tunnel construction, planning, and prefeasibility assessments.

Predicting Open TBM performance in hard rock is a long-standing challenge. Existing models like CSM and NTNU offer valuable estimates but require detailed geotechnical data, limiting their use in early project stages. To overcome these challenges of data-intensive methods, this study aims to develop a simplified, data-driven method using excavation diameter as the main input. By combining linear regression, random forest models, and Monte Carlo simulations (Hosseinzadeh, Abdollahi et al. 2024), the approach provides fast and reliable predictions of power, torque, and thrust. It serves as a practical tool for feasibility studies, TBM selection, and performance checks, complementing traditional models while improving efficiency, energy use, and cutter management in tunneling projects.

3.Exploratory Data Analysis (EDA)

The open TBM database presented in this paper serves as a valuable resource for assessing machine performance across a variety of ground conditions and tunnel geometries. It plays a crucial role in TBM feasibility studies by enabling comparisons between project-specific parameters and similar data within the database. However, the reliability of the database depends significantly on the quality of the original data. The database includes measurements for excavation diameter, power, thrust, and torque from 105 TBMs manufactured since 1985, drawing from a wide range of studies (Ozdemir 1977, Bilgin, Balci et al. 1999, GARSHOL, MELBYE et al. 2000, OKANO, WATABE et al. 2000, Chang, Choi et al. 2006, CHAPUIS and YIU 2006, Keiper, Crapp et al. 2010, Pompeu-Santos 2011, Bilgin, Copur et al. 2012, Moon and Oh 2012, Partov, Ivanov et al. 2012, Yazdani-Chamzini and Yakhchali 2012, Zhang, Qu et al. 2012, Cho, Jeon et al. 2013, Zhang, Kang et al. 2013, Ates, Bilgin et al. 2014, Rostami, Farrokh et al. 2014, Hassanpour, Rostami et al. 2015, Qi, Zhengying et al. 2016, Wilfing 2016, Park, Lee et al. 2018, Salimi, Faradonbeh et al. 2018, Sun, Shi et al. 2018, Salimi, Rostami et al. 2019, Yan-long and Lei 2021) , as shown in Fig. 1.

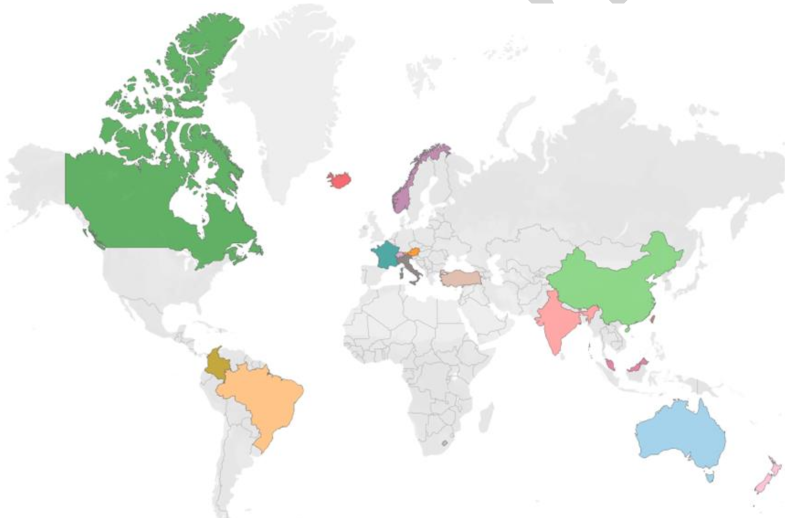

Fig. 1 *Geographic distribution of countries providing data on Open TBM dataset worldwide*

The primary objective of the Exploratory Data Analysis (EDA) was to explore the dataset, uncover key trends, identify outliers, and examine the relationships between significant variables. Fig. 2 shows histograms that were created for essential parameters such as excavation diameter, power, thrust, and torque.

The excavation diameter ranged from approximately 3 meters to 14 meters, with the majority concentrated between 4 and 6 meters, reflecting typical operational practices. Power requirements showed considerable variability, with most energy demand below 2000 kW. While extreme power requirements were rare, they could be substantial when they occurred. Thrust values varied widely, with most measurements falling below 15,000 kN, though a few outliers exceeded 20,000 kN. Similarly, torque values were generally below 10,000 kN·m, with some extreme cases reaching

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up to 17,500 kN·m. The presence of outliers in both thrust and torque highlights specific operational or geological challenges. These histogram insights will inform sensitivity analyses and model development, helping the models focus on significant trends while addressing data anomalies and variability effectively.

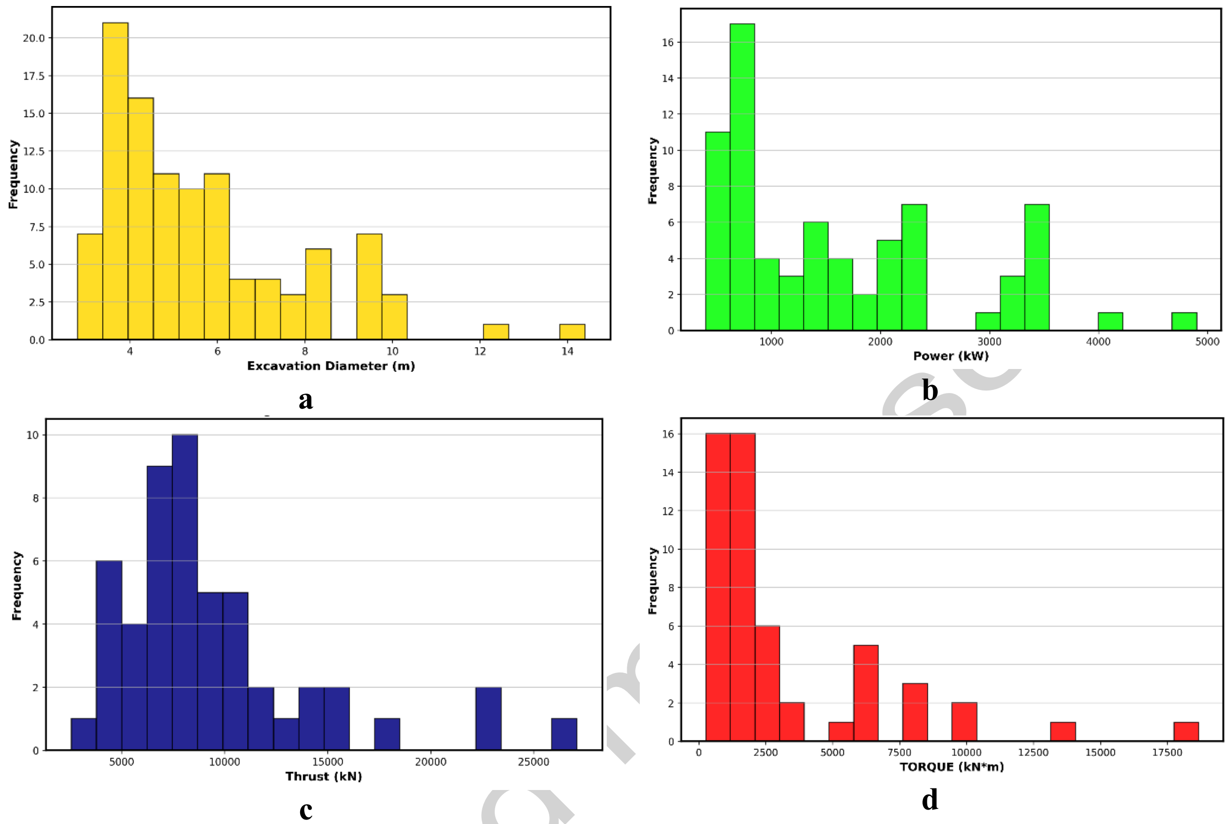

Fig. 2 *Histograms of a) Excavation diameter b) Power c) Thrust d) Torque*

Fig. 3 presents scatter plots illustrating the relationships between excavation diameter and the dependent variables—power, thrust, and torque. The visual representations revealed distinct patterns. Power exhibited a clear positive linear relationship with excavation diameter, suggesting that power increases proportionally as the excavation diameter expands. This linear trend highlights the predictability of power relative to tunnel diameter. In contrast, thrust exhibited a nonlinear positive relationship, with greater variability observed at larger diameters. This suggests that while thrust generally increases with tunnel diameter, other influencing factors contribute to its fluctuations. Finally, torque showed a strong positive correlation with excavation diameter, highlighting its direct dependence on the tunnel size and the mechanical effort required for excavation.

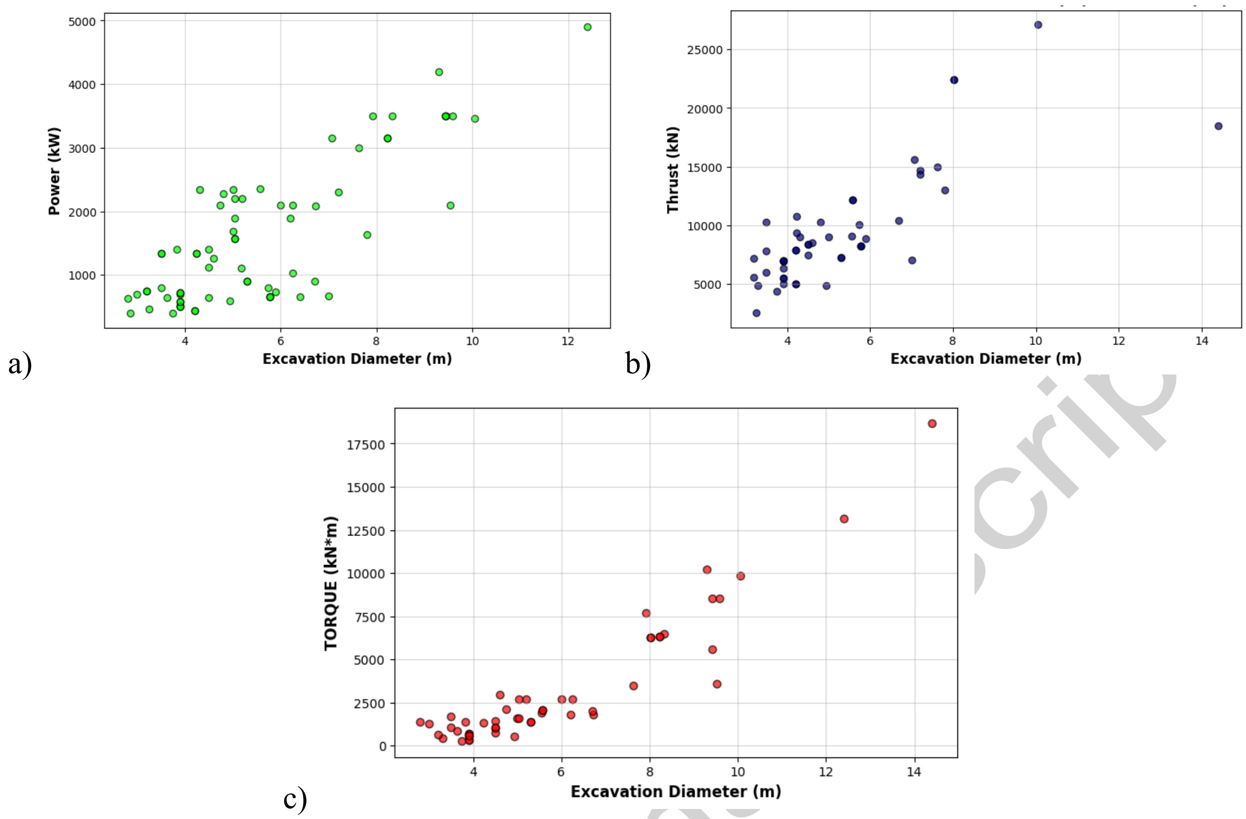

Fig. 3 Scatter plots of the connections between excavation diameter and the dependent variables: a) power, b) thrust, and c) torque

The correlation matrix depicted in Fig. 4 revealed a strong positive correlation (R = 0.93) between excavation diameter and torque, highlighting the pivotal role of tunnel size in determining torque. Similarly, a strong positive correlation (R = 0.82) was found between diameter and power, further reinforcing the proportional relationship observed in the scatter plot. Thrust exhibited a moderate positive correlation (R = 0.79) with diameter, consistent with the nonlinear variability observed in the scatter plot.

Fig. 4 Correlation matrix between Tunnel Diameter, Torque, Power, and Thrust

Additionally, the statistical analysis results demonstrate that linear regression effectively captures the relationships between diameter and the dependent variables, though the accuracy varies. Power showed a moderate fit with an R^2 of 0.6120, indicating that 61.2% of the variance in power can be attributed to excavation diameter. The Root Mean Squared Error (RMSE) of 632.19 kW and the Mean Absolute Error (MAE) of 449.75 kW suggest reasonable predictive accuracy, though there is room for refinement. Thrust displayed a strong fit, with an R^2 of 0.8491, meaning that 84.91% of the variance is explained by diameter. This robust relationship is further supported by relatively low error metrics (RMSE = 1348.84 kN and MAE = 1220.76 kN), indicating reliable and accurate predictive performance. In contrast, the correlation between torque and diameter was weaker, with an R^2 value of 0.4592, meaning diameter alone explains only 45.92% of the variance in torque. The higher RMSE of 1394.77 kN·m and MAE of 1072.52 kN·m suggest that additional explanatory variables or alternative modeling techniques, such as non-linear regression, may be needed to more effectively capture the variability in torque.

4.Monte Carlo Simulation

Monte Carlo Simulation (MCS) is a computational technique used to model and analyze systems with inherent uncertainty. Developed in the 1940s by scientists such as Stanislaw Ulam and John von Neumann during the Manhattan Project, MCS utilizes random sampling and statistical modeling. It draws its name from the Monte Carlo Casino due to its reliance on probability and chance, much like gambling (Lam and von Neumann 1940, Farzay, Khatibi et al. 2022, Farzay, Shakhouri et al. 2022).

This study aimed to investigate the relationships between diameter (input) and the outputs of power, thrust, and torque in TBM operations. The Diameter, treated as an independent variable, was modeled using a normal distribution based on its observed mean and standard deviation. Regression equations developed during the statistical modeling phase were employed to establish links between excavation diameter and the dependent variables, forming the basis for subsequent simulation. To account for variability, 10,000 random diameter samples were generated from the specified normal distribution. This extensive sampling comprehensively represented a typical and extreme excavation diameter, effectively capturing the real-world variability encountered in TBM operations. A large sample size, such as 10,000, was crucial for accurately encompassing the range of potential outcomes and identifying rare but significant events. Using these random diameter samples, the system was simulated by applying the regression equations for power, thrust, and torque to predict their respective outputs. The simulation process was repeated for all 10,000 samples, encompassing the full range of possible outcomes and providing valuable insights into the variability and distribution of these metrics. To maintain operational relevance, negative or unrealistic results were filtered out during the simulations. Fig. 5 depict the probabilistic distributions of performance parameters of open TBM in gathered data base.

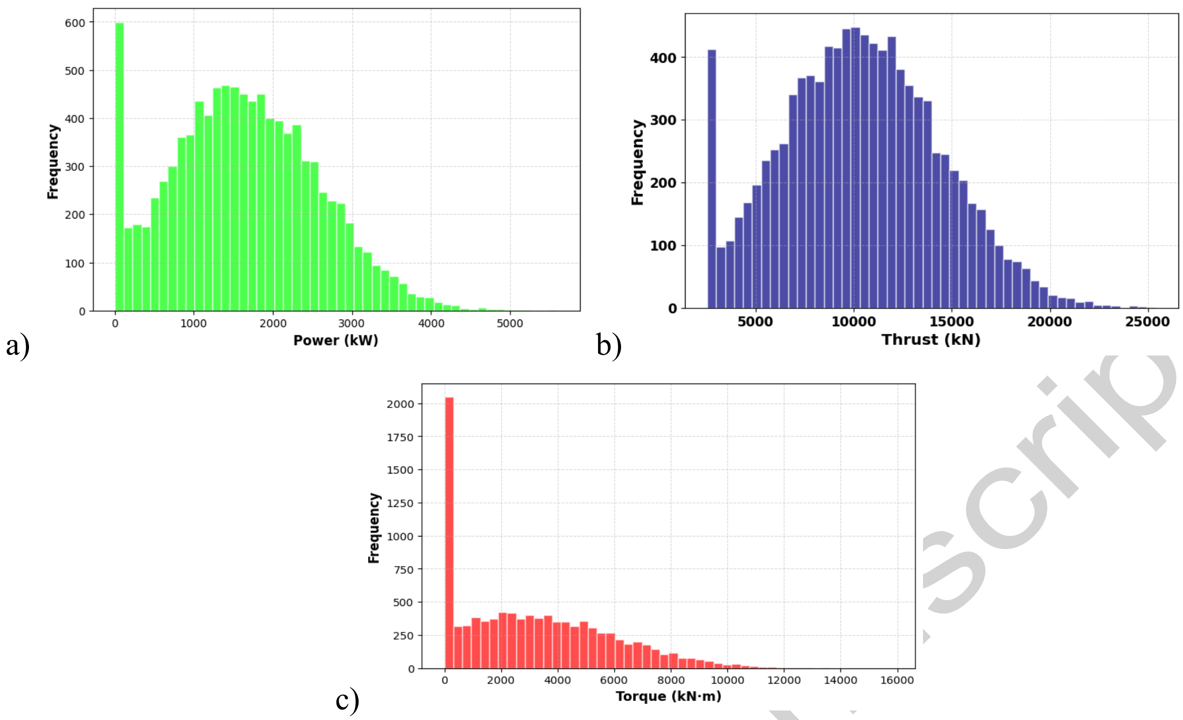

Fig. 5 *The probabilistic distributions of a) power, b) thrust, and c) torque*

The power simulation results (Fig. 5.a) show an average of 1666.30 kW, with a standard deviation of 891.97 kW and values ranging from 396.00 kW to 4958.44 kW. The histogram displays a right-skewed distribution, where most power values are concentrated below 3000 kW, reflecting moderate energy requirements during typical operations. A distinct peak at the lower end corresponds to scenarios with smaller tunnel diameters, while the higher power demands approaching 5000 kW are associated with extreme conditions involving larger diameters.

For thrust values (Fig. 5.b), the results show a mean of 10,297.71 kN, with a standard deviation of 4,082.22 kN, and range from 2,550.00 kN to 24,606.68 kN. The histogram exhibits an approximately normal distribution, with most values clustering around the mean of 10,000 kN, indicative of standard normal forces. Occasionally, extreme values exceeding 20,000 kN are observed, typically in scenarios involving larger diameters or complex geological conditions that require significant excavation force.

The torque results (Fig. 5.c) present an average of 3263.72 kN·m, with a standard deviation of 2644.02 kN·m, with values spanning from 260.00 kN·m to 13,764.15 kN·m. The histogram shows a highly skewed distribution, with a prominent peak near the minimum value, suggesting that most situations require only moderate torque levels. Rare instances of exceptionally high torque exceeding 13,000 kN·m indicate critical operational challenges linked to larger diameters or demanding excavation conditions.

5.Sensitivity Analysis

This analysis examines the impact of diameter variations on power, thrust, and torque. Specifically, the sensitivity of these metrics to changes in diameter was assessed by systematically adjusting the baseline diameter by ±1%, ±5%, and ±10%. A new Monte Carlo simulation was run for each adjustment to predict output metrics based on the modified diameter values. The simulation results were then compared to a baseline scenario with no diameter changes. Fig.6 illustrates the percentage variations in power, thrust, and torque, quantifying their sensitivity to changes in excavation diameter.

Power as illustrated in Fig.7 , shows a consistent and proportional relationship with diameter changes, where an increase in diameter significantly raises power requirements. For instance, a 10% increase in diameter results in a 12.06% rise in power, while a 10% decrease leads to a reduction of 17.66%. Fig. 8 displays notable sensitivity to diameter variations for thrust, with the random forest model capturing the complex, non-linear relationship between the variables. Random Forests split tunnel diameters into groups and predict each group's average thrust, so –1 % change can jump you into a group with a higher average and cause an artificial bump. Even with these little jumps, Random Forests still outperform, assuming a normal distribution because they learn the true non-linear, skewed relationships in data rather than forcing all thrust values into a smooth bell curve. A 10% decrease in diameter yields a substantial 26.04% reduction in thrust, while a 10% increase causes a significant decrease of 17.41%. Fig. 9 shows torque is the most sensitive metric to diameter changes, with pronounced fluctuations. A 10% increase in diameter results in a 13.80% rise in torque, whereas a 10% reduction causes a significant drop of 35.53%.

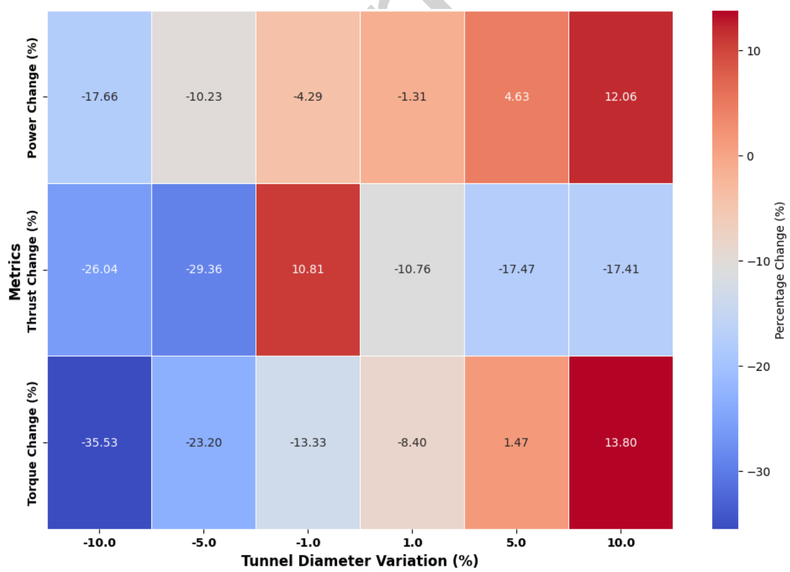

Fig.6 *correlation matrix of sensitivity analysis*

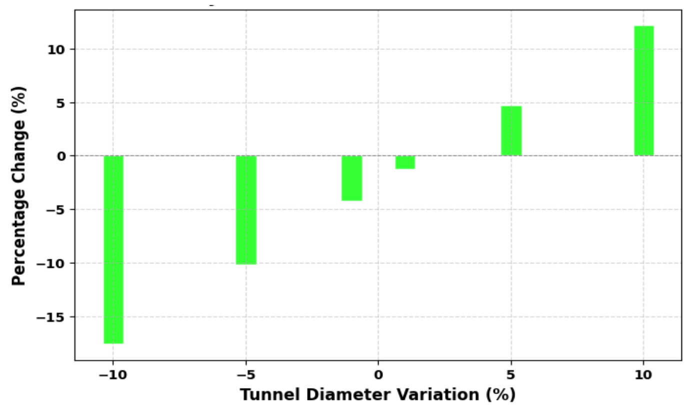

***Fig.**7 Sensitivity of power to diameter variation*

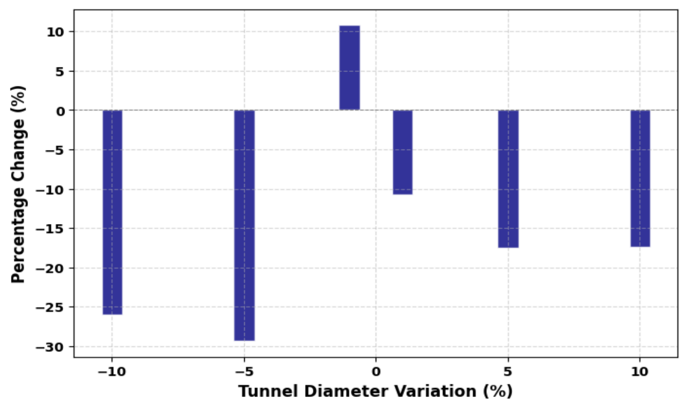

***Fig. 8** Sensitivity of thrust to diameter variation (random forest)*

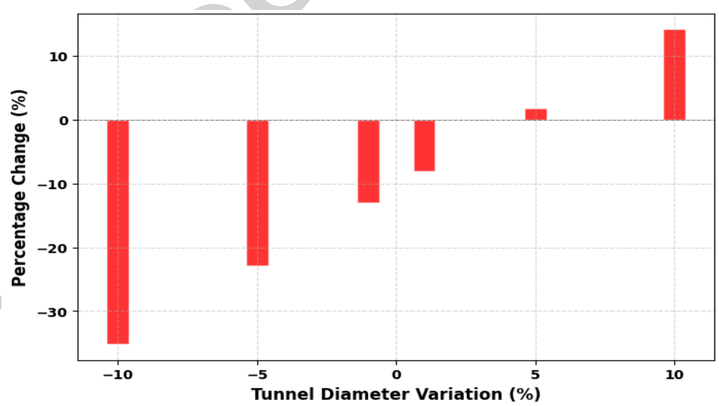

***Fig. 9** Sensitivity of torque to diameter variation*

6.Results and Discussion

This study highlights the critical role of excavation diameter in determining power, thrust, and torque in Open TBM operations. EDA confirmed a strong linear relationship between diameter and power, while torque and thrust exhibited moderate correlations. Correlation analysis further reinforced these findings, showing a strong positive correlation between diameter and torque (R = 0.93) and diameter and power (R = 0.82), while thrust (R = 0.79) displayed more variability, indicating the influence of additional factors.

Statistical modeling demonstrated that linear regression effectively predicted power ($R^2 = 0.6120$) and torque ($R^2 = 0.4592$), whereas thrust required a non-linear approach, with a random forest model achieving an R^2 of 0.8491, better capturing its variability.

Monte Carlo simulations (10,000 diameter samples) helped define the operational range of these metrics:

- Power: 1666.30 kW (σ = 891.97 kW), range 396.00 – 4958.44 kW.
- Thrust: 10,297.71 kN (σ = 4,082.22 kN), range 2,550.00 – 24,606.68 kN.
- Torque: 3263.72 kN·m (σ = 2644.02 kN·m), range 260.00 – 13,764.15 kN·m. Extreme values in thrust and torque indicated operational challenges linked to larger diameters or complex ground conditions.

Sensitivity analysis provided further insights:

- 10% diameter increase→ Power +12.06%, Torque +13.80%, Thrust -17.41%.
- 10% diameter decrease→ Power -17.66%, Torque -35.53%, Thrust -26.04%.
- Torque is the most sensitive to diameter changes, while power maintains a proportional response.

These findings have practical applications across different phases of TBM projects. The model can be used in feasibility studies to validate performance predictions and in final assessments to cross-check forecasts made using CSM and NTNU models. Additionally, in cases requiring auxiliary or emergency tunnels, where historical performance data is available, this model provides a fast and reliable method for assessing the impact of diameter adjustments.

Some limitations should be acknowledged regarding the findings of this study. Firstly, the dataset utilized in this study includes some older data, which might not fully reflect recent advancements in TBM technology; updating and reevaluating these data could enhance model precision. Secondly, the advancement rates used are averaged from multiple measurements rather than constant values, introducing variability that may affect predictive accuracy. Additionally, the sensitivity analysis for thrust may require careful interpretation, as it does not explicitly specify the percentage of total possible thrust applied to the TBM cutterhead, potentially influencing the reliability of sensitivity results. Lastly, since the dataset was compiled from multiple publications as cited in the EDA analysis, the overall reliability of data is assumed to be valid based on original sources but cannot be independently verified within this study.

7.Conclusion

This study developed a simple, data-driven approach to predict Open TBM performance in hard rock, mainly using excavation diameter. Combining linear regression, random forest models, and Monte Carlo simulations showed that diameter strongly affects power, thrust, and torque. Torque was most sensitive to diameter changes, highlighting its importance for TBM design and operations.

The approach is practical and can help engineers quickly validate performance predictions, select suitable TBMs, and optimize efficiency. However, the study had some limitations, including data not being recent, which could affect accuracy. Future studies should update the database with recent measurements and provide more detailed analysis of thrust usage to improve model reliability.

8.Declaration

The authors declare that ethics approval and consent to participate are not applicable. All authors have provided consent for the publication of this manuscript. The authors declare no competing interests. This research was not funded. Oveis Farzay designed the study and performed the statistical analysis. Seyedkhashayar Jamali collected the data and conducted the literature review. Marilena Cardu designed the study and reviewed the results. The datasets used and/or analyzed during the current study are available from the articles cited within the manuscript.

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