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Physics-informed theory modelling of rock engineering features from TBM operational data

H. Samadi[1] & A. Danzi[2]
[1] *R&D Specialist, R&D Department, SYSTRA S.p.A., Italy*
[2] *Head of IT and R&D Department, SYSTRA S.p.A., Italy*
adanzi@systra.com

Abstract

Accurate determination of rock engineering parameters is important for reliable prediction and optimization of tunnel boring machine (TBM) performance. In this study, TBM performance indicators and operational parameters are used to infer key geomechanical properties, including both intact rock and rock mass characteristics, across several lithological units (e.g. Paragneiss, Amphibolite, and calc- phyllite-schist with low to high grade of metamorphism) encountered along the Brenner Base Tunnel (BBT) alignment that connects the cities of Innsbruck (Austria) and Fortezza (Italy). The dataset, derived from both pre-construction investigations and construction-phase monitoring, is divided into geological zones and lithological units, with representative ranges of considering operational parameters and rock mechanical features defined for each zone.

A framework based on physics-informed theory, engineering mechanics, and stacking ensemble learning model are developed to establish simulation between machine response, mechanical specifications, and ground conditions. The meta-learner stacking logic is implemented using the ridge cross-validation (RidgeCV) and the ensemble is built on three high-performance tree-based algorithms, including extra trees regressor (ET), hist gradient boosting regressor (HGB), and gradient boosting regressor (GB) based on the polynomial interaction technique. They were selected because they handle geological noise and non-linear relationships differently, therefore, providing a balanced prediction of rock mechanical features. The proposed modeling approach shows predictive accuracy, yielding reliable estimates of rock engineering properties and supporting its applicability to future double shield (DS)-TBM operations in metamorphic rock units.

Keywords

Rock engineering, Ground assessment, Tunnel, TBM, Rock-machine interaction.

1 Introduction

Establishing relationships between tunnel boring machine (TBM) parameters and rock mechanical factors under rock ground conditions through forward analysis has been investigated in several studies (Rostami, 1993; Bruland 1998; Barton 2000; Hassanpour et al. 2011; Samadi et al. 2024). However, analyzing rock mechanical factors based on historical TBM performance data through reverse (back) analysis is more complex due to the nonlinear interactions between rock–machine parameters and continuously changing ground conditions. Such analyses require advanced methodologies. To the best of the authors' knowledge, most previous studies have focused on forward analysis, using rock mechanical parameters to predict machine performance, which differs from the scope of this study. This work proposes an approach based on reverse analysis, which has not been adequately addressed in the literature. To overcome these limitations, the present study aims to simulate key rock mass and intact rock parameters from historical TBM performance data from the Brenner Base Tunnel (BBT) project using a coupled physics-informed modelling and stacking ensemble learning model.

2 Project Description

The Brenner Base Tunnel (BBT) is a major railway project that connects Innsbruck in Austria to Fortezza in Italy. It is a joint effort between the two countries, with additional support from the European Union. The tunnel is about 55 km long and runs beneath the Eastern Alps, passing under the Brenner Pass (BBT 1999). Due to its length, the BBT is considered the longest railway tunnel in the world. The tunnel system consists of two main parallel tunnels and an exploratory tunnel. This study focuses on Lot Mules 2–3, specifically the west tunnel (GLON-T2). Excavation in this section was carried out using a TBM (STBM-1071) manufactured by Herrenknecht. The machine has an excavation diameter of 10.7 m and is equipped with 64-disc cutters on the cutterhead. The cutters are spaced at an average of about 90 mm and are designed to apply a thrust force of 176 kN each (cutter load, thrust force per each cutter). More detailed technical specifications of the TBM are provided in Table 1.

Table 1. A detailed description of HR-STBM1071 specifications.

Parameters		**Symbol**	**Value**	**Unit**
Cutterhead	Diameter	D	10710	mm
	Diameter	Ds	10650	mm
Front shield	Length	L	4820	m
	Width	W	80	mm
	Diameter	Ds	10440	mm
Middle shield	Length	L	4150	m
	Width	W	50	mm
	Diameter	Ds	10420	mm
Tail shield	Length	L	2520	m
	Width	W	80	mm
	Number of disc cutters	N_{dc}	64	-
Cutting tools	Disc cutter size	D_{ds}	19	in
	Spacing	S_{ds}	90	mm
Thrust system	Thrust force	TF	112815	kN
Torque	Cutterhead torque	CT	13600*, 27524**	kN.m
Rotation speed	Cutterhead rotation speed	RPM	0-5.11*, 0-2.55**	rpm

Note: Gear I*, Gear II**, nominal values

The Lot Mules 2–3 section (including the GLON tunnel) passes through several different geological formations. One of the most complex areas is the Periadriatic Line, which represents the boundary between the African and European tectonic plates. This zone includes geological intrusions with relatively weak mechanical properties, which makes excavation more difficult. Along this section, the GLON tunnel mainly crosses metamorphic rocks with different levels of metamorphism, from low to high grade. The most common rock types are paragneiss, amphibolite, and calc-phyllite–schist. The geological profile of the studied tunnel section is presented in Fig. 1. Based on laboratory tests and in-situ investigations, the uniaxial compressive strength (UCS) generally ranges from about 33 MPa to 107 MPa, although values up to 140 MPa have been recorded along the entire tunnel alignment. The rock quality designation (RQD) varies from very low values of around 10 up to about 34.

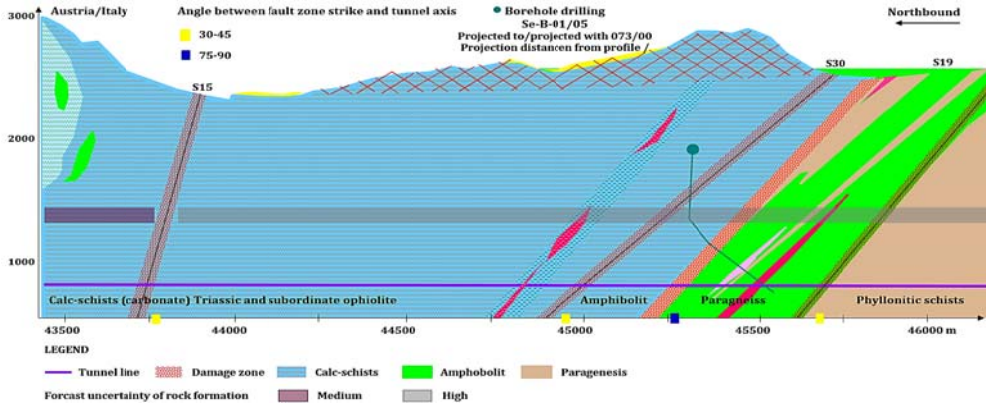


Fig. 1 Geological profile of the GLON tunnel (chainage 43+500 km to 46+000 km).

3 Data Analysis

The dataset used in this study was obtained from the Lot Mules 2–3 (GLON tunnel) project and includes both TBM operational records and rock mass geomechanical data. The TBM-related variables cover cutterhead torque (CT), rotation speed (RPM), penetration per revolution (Pr), cutter load (Fn), cutterhead power (P), and specific energy (SE). In addition, key machine characteristics such as cutterhead diameter and the number of disc cutters were also considered. On the geological side, important rock parameters such as UCS, RQD (Deere 1988), rock mass rating (RMR) (Bieniawski 1989), geological strength index (GSI) (Hoek 1994), and joint volumetric count (Jv) (Palmstrom 1982) were included. After data cleaning and preprocessing and applied principal component analysis (PCA), as well as TBM performance theory and engineering judgement, the final dataset was structured into a 1020 × 11 matrix (reduced from an initial raw dataset of 5500 × 20 variables). This dataset combines both machine performance indicators and rock engineering parameters.

In the modeling framework, rock mechanical properties (including both intact rock and rock mass characteristics) were treated as multi-output targets, while TBM operational variables were used as inputs to capture the interaction between the machine and the surrounding ground conditions. If a dataset for machine learning (ML) analysis is organized by stratigraphic sequence or ring numbers, a model may unintentionally learn the order of the data rather than the true physical relationships between rock parameters and machine performance. To avoid this issue, the data were shuffled so that both the training and testing sets include a well-balanced mix of different geological conditions. This approach helps reduce spatial bias, which can otherwise lead to overly optimistic training results but weak performance when applied to new, unseen data. Moreover, because the chosen models in section 4. Methodology treats each sample independently, the random shuffling adopted to balance geological conditions across the splits fully maintains the integrity of the analysis. The detailed descriptive statistics for each parameter are summarized in Table 2.

Table 2. Statistical descriptive measurement for each parameter used in the database.

Parameter	CT	RPM	Pr	Fn	P	SE	UCS	RQD	Jv	GSI	RMR
Average	2.4	3.1	12.2	221.5	932.3	14537.9	63.4	29.8	25.8	46.5	45.5
Maximum	9.5	5.2	26.5	471.0	1599.1	42042.5	107.0	34.0	31.8	55.0	55.0
Minimum	0.7	0.9	5.7	65.9	40.0	5016.9	33.0	10.0	24.5	33.0	28.0
Std. Dev	0.8	1.0	3.3	51.4	259.0	5259.2	21.8	6.8	2.1	6.6	7.0
Variance	0.7	1.0	10.8	2638.6	67083.9	27659393.4	477.2	46.5	4.3	44.0	49.5
Kurtosis	12.1	-1.3	0.1	0.7	-0.2	3.0	-0.4	2.7	2.6	-1.2	-0.1
Skewness	2.5	0.5	0.5	0.3	-0.3	1.3	0.6	-1.9	1.8	-0.1	-0.7
Median	2.3	2.6	12.4	215.8	960.4	13458.1	55.0	33.0	24.8	45.0	46.0
Count	1020	1020	1020	1020	1020	1020	1020	1020	1020	1020	1020
Type	Inputs						Outputs				
Unit	MN.m	rpm	mm/rev	kN	kW	MJ/m^3	MPa	-	*Joints/*m^3	-	-

4 Methodology

The data were collected from metamorphic rock formations (low to high metamorphism grade). In total, 1020 data samples were available for each geological section and excavation ring, forming a dataset suitable for analysis. The dataset was divided into two parts: 85% of the data (867 samples) were used for model training, while the remaining 15% (153 samples) were reserved for testing. In this study, the meta-learner stacking logic is applied using the ridge cross-validation (RidgeCV) and the

ensemble is built on three high-performance tree-based algorithms, including extra trees regressor (ET), hist gradient boosting regressor (HGB), and gradient boosting regressor (GB) based on the polynomial interaction technique. To reach a valid accuracy rate for 15% test subset of database, several techniques including polynomial interaction mapping (before training the model), standard scaling, multi-output wrapper, and data shuffling were applied. Multi-output wrapper was used because the database predicts five distinct targets (UCS, RQD, Jv, GSI, RMR) simultaneously, and this technique ensures that the stack is optimized for the unique physical distribution of each rock engineering property. Details of the model structures and configurations is provided in Table 3.

Table 3. The structure and configuration to create the stacked model.

Structure	Model	Description
Data pre-processor	Standard scaler and Polynomial features	degree=2, interaction-only=True, include-bias=False
Base expert 1	Extra trees regressor (ET)	n-estimators=1000, max-depth=15, random-state=42
Base expert 2	Gradient boosting (GB)	n-estimators=500, learning-rate=0.05, max-depth=5, random-state=42
Base expert 3	Hist gradient boosting (HGB)	Max-iter=1000, random-state=42
Meta-learner	RidgeCV	Cv = 5, L2-regularized linear regression
Output wrapper	Multi output regressor	Parallelizes the stack to create 5 distinct prediction engines for UCS, RQD, Jv, GSI, and RMR

5 Results and Discussion

The comparison between the model's predictions against the actual observed field values is presented in Fig. 2. Based on the results of evaluation metrics such as A-20 and root mean square error (RMSE), the models appear to perform very well, as the points closely follow the identity line (categorical rather than continuous). The rock mechanical properties along the tunnel route are categorical because they remain constant within each distinct geological unit, changing only when transitioning into a new geological formation, structure, or zone.

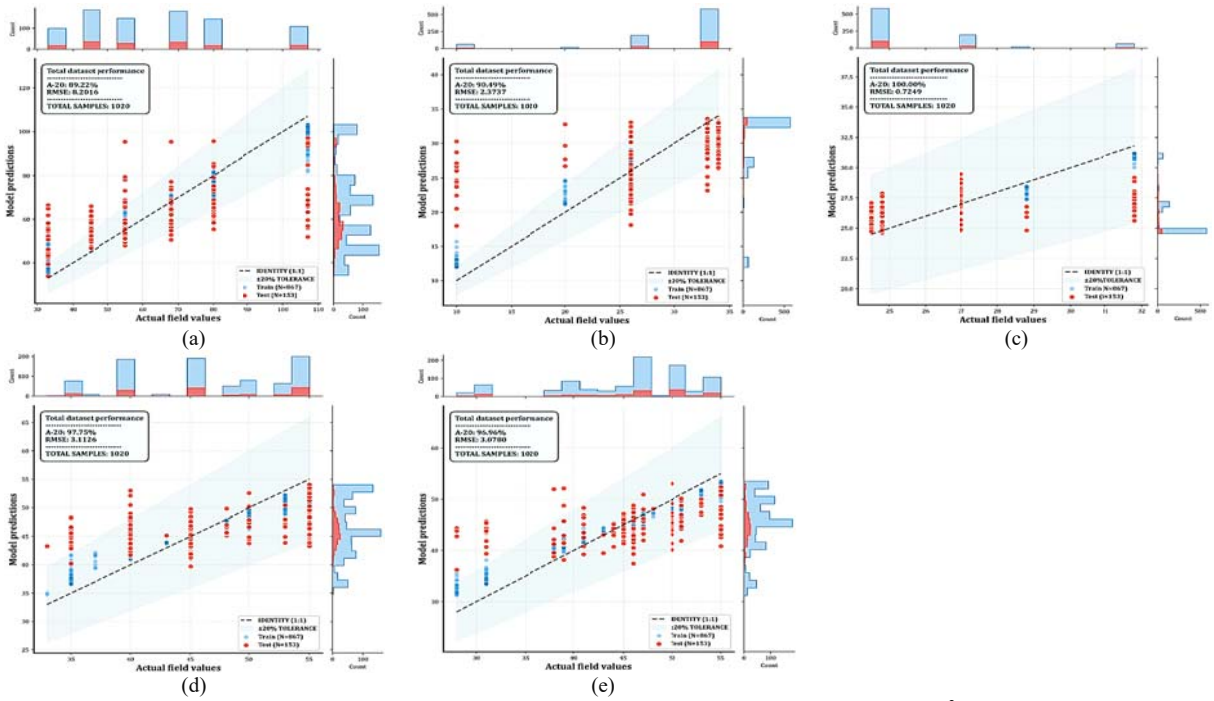


Fig. 2 Comparison between predicted and actual values, (a) UCS (MPa), (b) RQD, (c) Jv (joints/m^3), (d) GSI, (e) RMR.

Additionally, SHapley Additive exPlanations (SHAP) analysis was performed as a tool within explainable AI (XAI). The SHAP results, presented as distribution plots for all outputs, are shown in Fig. 3. These results show how the input features (primarily the first two machine factors) contribute to optimizing the system and provide the control over the outputs in the physics-informed modelling.

Physics-informed modelling (post-hoc interpretability, coupled feature interaction) was applied to all input parameters in the database across all possible scenarios to establish relationships between rock mechanical features and historical TBM performance data. However, due to the page limitations of Eurock 2026, only a representative example of the coupled physics-informed modelling is provided.

Fig. 4 presents the two-dimensional (2D) version, while Fig. 5 shows the three-dimensional (3D) version. The example is based on the two most influential factors identified through the SHAP analysis for each output variable.

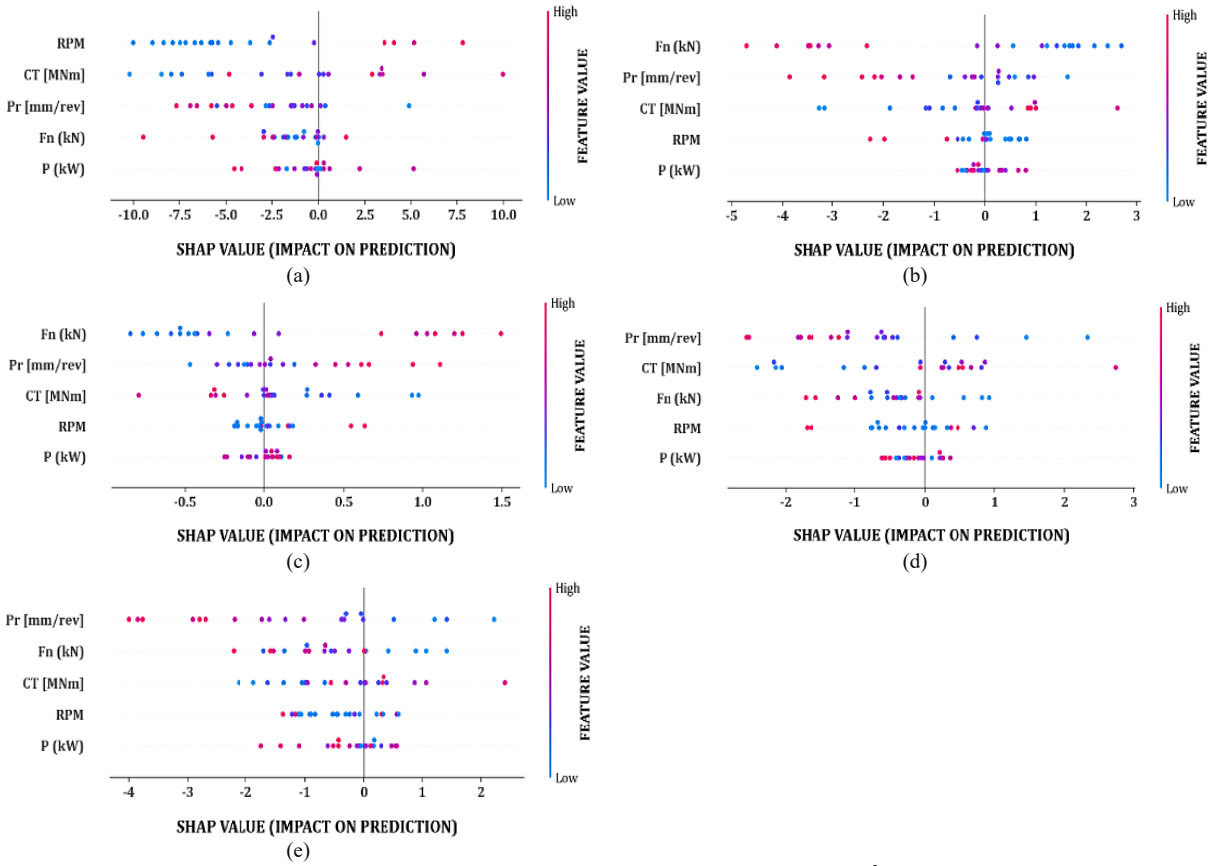


Fig. 3 Results of interpretability SHAP analysis, (a) UCS (MPa), (b) RQD, (c) Jv (joints/m^3), (d) GSI, (e) RMR.

The 3D visualization of the predicted values of all rock mechanical factors for each tunnel segment (1020 installed segments) along the entire tunnel alignment was carried out using four output simulation layouts: resultant force (stress gradient), deformed mesh (wireframe), contour lines (banded), and total difference (projected) (Fig. 6). However, due to the page limitations, only a representative example is presented. The example focuses on RMR, as it considers both intact rock and rock mass properties and serves as a reliable indicator of rock mechanical characteristics.

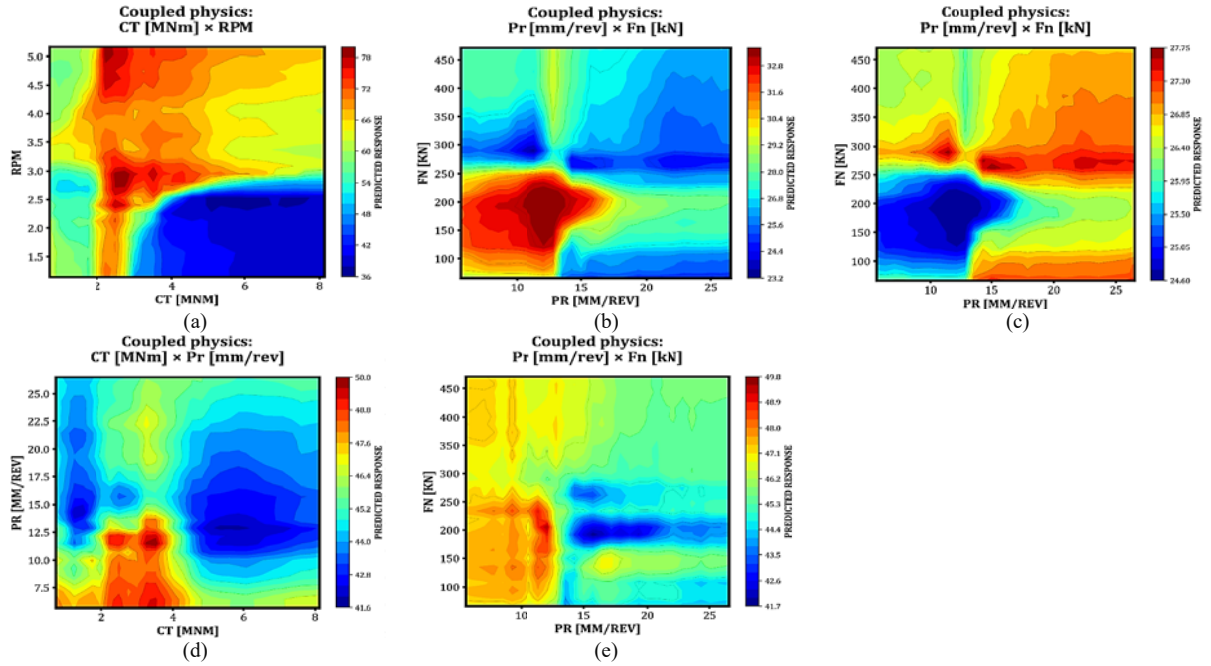


Fig. 4 2D coupled physics-informed modelling (the most important factors in SHAP analysis per each output parameter), (a) UCS (MPa), (b) RQD, (c) Jv (joints/m^3), (d) GSI, (e) RMR.

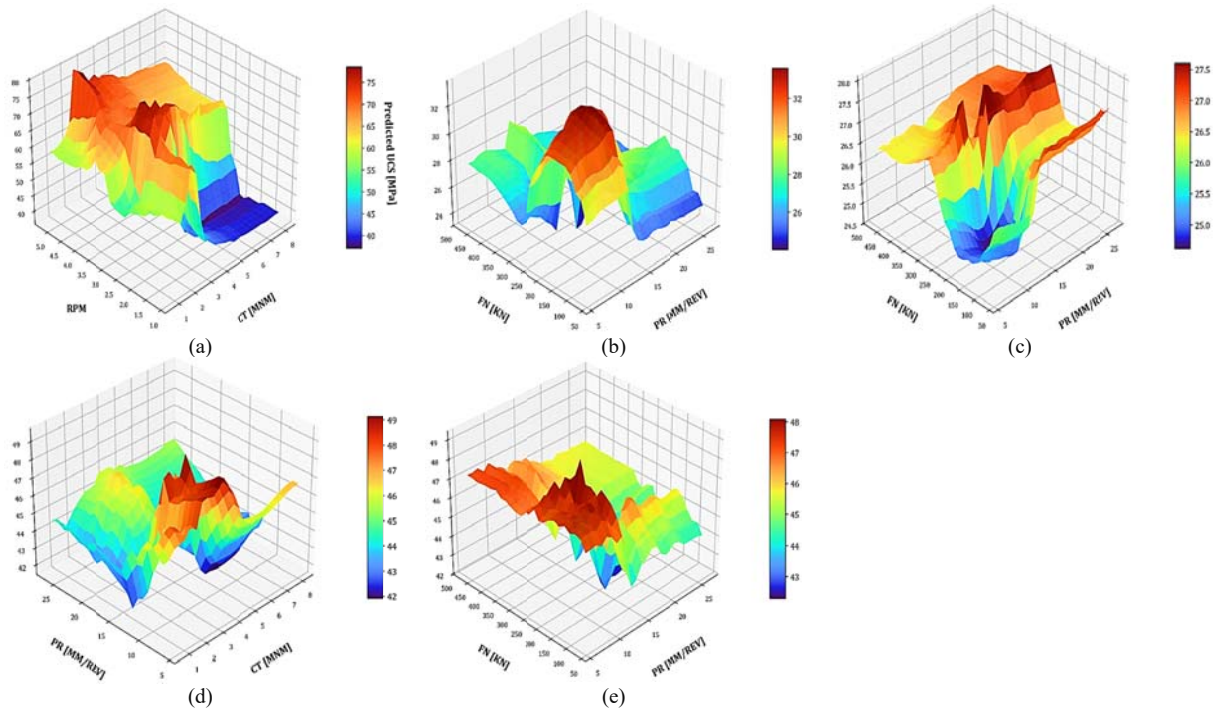


Fig. 5 3D coupled physics-informed modelling (the most important factors in SHAP analysis per each output parameter), (a) UCS (MPa), (b) RQD, (c) Jv (joints/m^3), (d) GSI, (e) RMR.

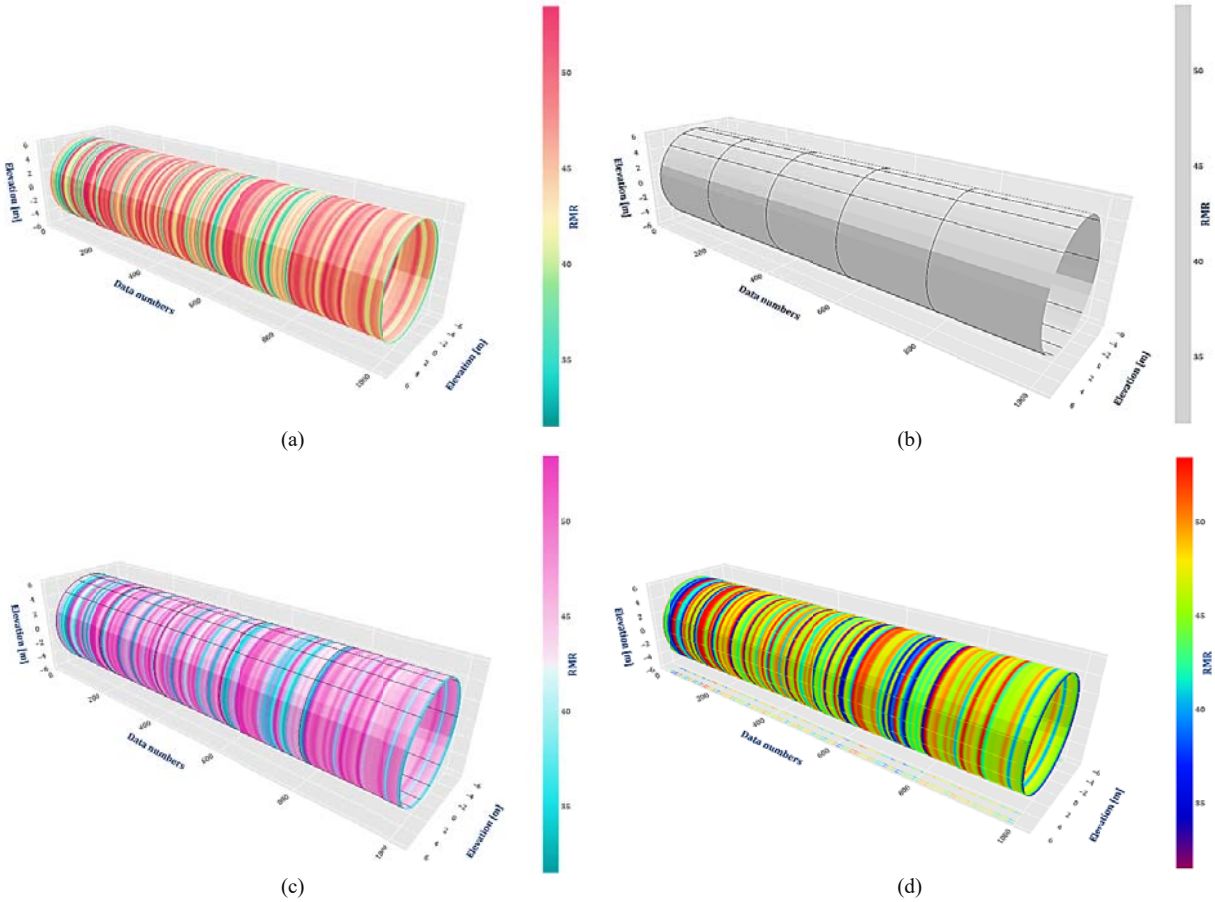


Fig. 6 3D visualization of RMR prediction values per each tunnel segment through the whole tunnel layout, (a) resultant force, (b) deformed mesh, (c) contour lines, (d) total difference.

6 Conclusions

This study presented a framework for the back-analysis of rock engineering parameters using historical TBM performance data. A coupled approach integrating physics-informed modelling with a stacking ensemble learning model was developed to capture the complex, nonlinear interactions between machine behavior and ground conditions. The ensemble model, built on Extra trees, hist

gradient boosting, and gradient boosting regressors with a RidgeCV meta-learner, showed strong predictive capability. Evaluation results, including A-20 and RMSE metrics, confirmed a high level of agreement between predicted and observed values (categorical rather than continuous). Furthermore, XAI using SHAP analysis was done to investigate the impact of each feature on the outputs to make the model more interpretable and explainable. The integration of stacking explainable AI with physics-informed modelling provides deeper insight into rock–machine interaction mechanisms and improves confidence in model perdition.

References

Barton NR (2000) TBM tunnelling in jointed and faulted rock. Balkema, Rotterdam. Crc Press. p.173.

BBT (1999) Project overview. URL: https://www.bbt-se.com/en/tunnel /project- overview/.

Bieniawski ZT (1989) Rock mass classifications: A complete manual for engineers and geologists in mining, civil, and petroleum engineering John Wiley & Sons: Toronto, ON, Canada.

Bruland A (1998) Hard rock tunnel boring. Ph.D. Thesis. Norwegian University of Science and Technology,Trondheim.

Deere D (1988) The rock quality designation (RQD) index in practice. InRock classification systems for engineering purposes: 91-101. ASTM International.

Hassanpour J, Rostami J, Zhao J (2011) A new hard rock TBM performance prediction model for projectplanning. Tunnelling and Underground Space Technology 26(5):595-603. https://doi.org/10.1016/j.tust.2011.04.004

Hoek E (1994) Strength of rock and rock masse. ISRM News Journal 2(2): 4-16.

Palmstrom A (1982) The volumetric joint count—a useful and simple measure of the degree of jointing. In Proceedings of the fourth international congress IAEG V:221-228.

Rostami J (1993) A new model for performance prediction of hard rock TBMs. In Proceedings 1993 rapid excavation and tunnelling conference (RETC).

Samadi H, Karimi H, Khamehchiyan M, Hassanpour J (2024) Prediction of engineering characteristics of rock masses using actual TBM performance data with supervised and unsupervised learning algorithms (a case study in strong to very strong igneous and pyroclastic rocks). Rock Mechanics and Rock Engineering 57(9):7223-7252. https://doi.org/10.1007/s00603-024-03903-9