Managing Squeezing Rock Mass with TBM Data Analysis: Rail Link Rishikesh – Karnaprayag (India)

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Abstract

The 125.2 km rail link Rishikesh–Karnaprayag in the Lesser Himalayas of India represents a benchmark in mechanized tunnelling through complex geology. This paper focuses on Tunnel 8, a 14.58 km section excavated primarily using two single-shield hard rock tunnel boring machines (TBM) under challenging conditions characterized by tectonically deformed, partly water-bearing phyllites and high in-situ stresses, thus squeezing rock mass conditions were at hand. Both TBMs were equipped with advanced instrumentation, including a Void Measuring System (VMS) for real-time monitoring of shield gap size and tunnel wall deformation rates - an unprecedented application in single-shield TBM tunnelling. An integrated, near–real-time data analysis framework was developed to continuously assess TBM operational parameters, enabling proactive control and optimization of excavation performance. Within that framework, the VMS data was used to run a novel analytical model-based squeezing risk monitoring system which integrates gross TBM advance rate, tunnel wall deformation rate, shield length, and shield gap size. Additionally, tunnel seismic prediction was employed to characterize the geology ahead of the face, and supervised machine learning algorithms were implemented for rapid interpretation and visualization, facilitating informed decision-making by TBM operators. The project demonstrates how advanced monitoring systems and data-driven tunnelling can significantly enhance TBM performance and risk management in geotechnically adverse conditions. Key operational insights and recommendations are provided to guide future large-scale TBM projects in similar geological environments.

Keywords: TBM excavation, Squeezing Ground, Hard Rock, Data Analysis, Machine Learning

Highlights

- Data-centric tunnelling optimized TBM performance in complex Himalayan geology.
- Unprecedented monitoring of shield gap in hard rock shielded TBM excavation.
- Analytical model developed to permanently monitor squeezing risk during excavation.
- Seismics and machine learning used to predict excavation conditions ahead of face.

1. Introduction

On the one hand, tunnel boring machines (TBM) have become the excavation- and tunnel construction method of choice for long tunnels (> 2km) in mostly homogeneous hard rock ground conditions (Maidl et al., 2008; Maidl et al., 2013; Bobet and Einstein, 2024) due to cost benefits. On the other hand, also in these conditions, squeezing rock mass can occur, which can pose significant threats to a TBM excavation (Barla, 2001; Ramoni and Anagnostou, 2010, 2011), ranging from reduced excavation performance to downtimes of several months in case a TBM gets fully stuck. According to Barla (2001) (see therein for earlier references) squeezing "*stands for large time-dependent convergence during tunnel excavation. It takes place when a particular combination of induced stresses and material properties pushes some zones around the tunnel beyond the limiting shear stress at which creep starts. Deformation may terminate during construction or continue over a long period of time.*" Conventionally, squeezing is dealt with by special measures like shield lubrication which may or may not work well (Erharter et al., 2023) or simply by adapting the TBM operation accordingly which means maintaining a minimum gross advance rate and avoiding longer foreseeable stops (e.g. cutterhead- or conveyor belt maintenance) in areas of squeezing rock mass conditions. Availability of comprehensive information about the state of the TBM excavation is the key to overcoming challenging ground conditions by operational optimization.

While on-site observations remain a major source of that information, modern TBMs are equipped with hundreds of sensors that continuously record a wealth of data - the TBM operational data. TBM operational data comprehensively represents the system behavior of an ongoing TBM excavation (i.e. the interaction of the TBM with the rock mass (Erharter et al., 2025b)) as it is the product of three main influences: the rock mass, the TBM machinery and the way the TBM is operated (Figure 1).

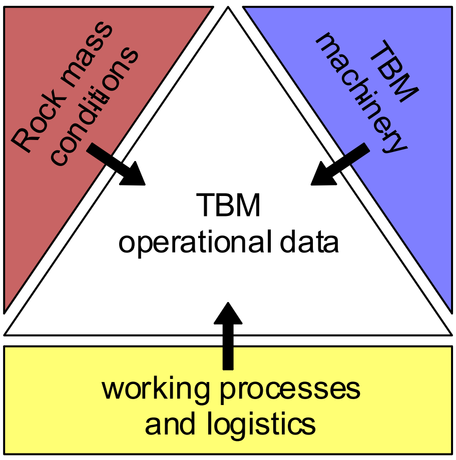

Figure 1: Main influences on TBM operational data (figure from Erharter et al. (2025b), licensed under CC BY-SA 4.0, unmodified).

Consequently, TBM operational data can be used as a main source of information for TBM excavation and system behavior monitoring. This contribution focuses on using TBM operational data to overcome challenging ground conditions and presents results from the case study of the Rishikesh-Karnaprayag project (India) where squeezing rock mass conditions of the lesser Himalayas were tackled with two single shield TBMs. While general state-of-the-art TBM operational data monitoring was conducted for this project (see Erharter et al. (2025b) for elaborations on modern TBM operational data processing), the Rishikesh-Karnaprayag project went beyond that by i) developing and implementing a data-driven methodology for early detection of squeezing in the shield area of a TBM and ii) developing and implementing a machine learning (ML)-based method to predict exceptional advance conditions ahead of the TBM. The two goals are illustrated in Figure 2.

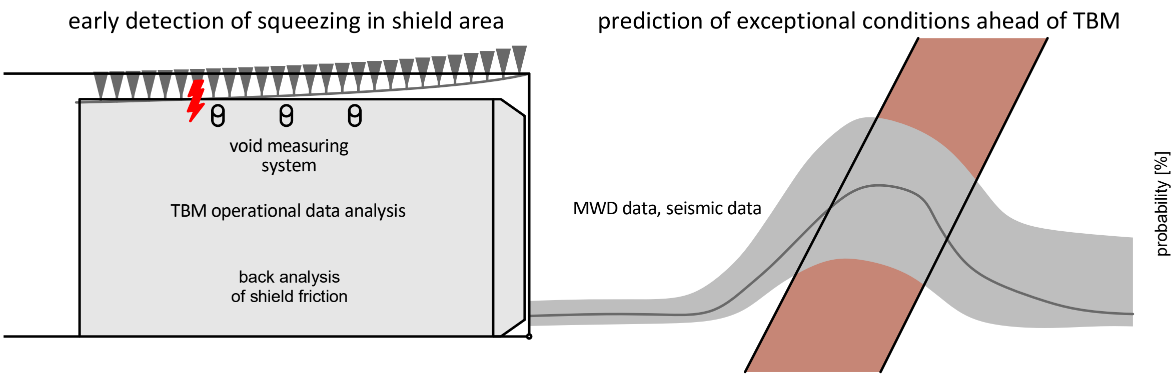

Figure 2: Schematic of the two data-driven development goals for the Rishikesh-Karnaprayag project. Left: an early detection system for squeezing in the shield area, right: a system to predict exceptional conditions ahead of the TBM.

The work that was conducted at the Rishikesh-Karnaprayag project is a valuable case study as it pushed the boundaries of what can be achieved with TBM operational data monitoring today and thus serves as a role model for future projects in similar conditions. Section 2 will give a general outline of the project and its geology, information about the deployed TBMs (which were equipped with unconventional sensory systems) and a description of the encountered challenging rock mass conditions. Based on these prerequisites, a fully automatic data processing framework was developed together with a new analytical method for predicting squeezing risk for single shield TBMs, as well as a ML-based prediction system that forecasts exceptional advance conditions. These methodological explanations will be given in section 3. Section 4 will show the observations that were made on-site using these methods, which includes one of the first ever reports of a continuous tunnel wall deformation record for a single shield TBM tunnel drive. The TBM operational data-related developments and observations from the Rishikesh-Karnaprayag project will then finally be discussed in section 5 and conclusions and recommendations for future projects are provided in section 6.

2. Project Overview and Background

2.1. Rail Link Rishikesh – Karnaprayag

Rail Vikas Nigam Limited (RVNL), a navratna CPSU under Ministry of Railways, is constructing the 125.2 kilometers long Rishikesh-Karnprayag Railway Project. The route is in the Indian state of Uttarakhand and goes in a north-eastward direction from the existing Virbhadra Railway Station near Rishikesh and culminates at newly designed Karnprayag Railway Station. The project comprises 213.45 kilometers of tunnelling, including 16 main tunnels, 13 escape tunnels, 7 adit tunnels, and numerous cross passages, traversing along the fragile and seismically active Himalayan belt, following the Ganga and Alaknanda River valleys, where the rugged topography and geological complexities demand some of the most advanced tunnelling and construction methodologies available today. This paper reports on developments and observations from "Tunnel 8" of the project which connects Devprayag Railway Station with Janasu Railway Station through a 14.58 km double line tunnel. An overview map of the whole project and the location of Tunnel 8 is given in Figure 8.

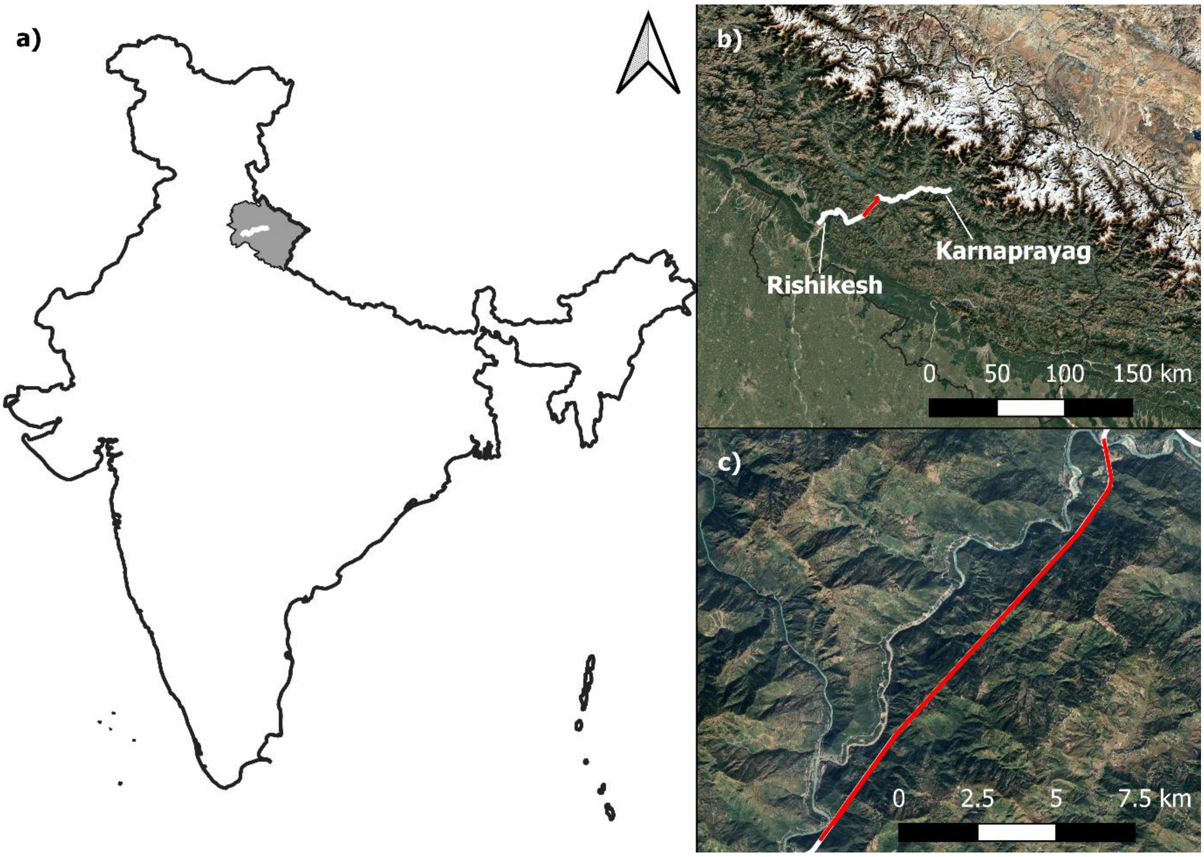

Figure 3: Overview map. a) position of the Rishikesh-Karnaprayag route section (white) within the Indian state of Uttarakhand (grey). b) detail view of the route section in within Uttarakhand, tunnel 8 in red. c) detail view onto Tunnel 8 along the Alaknanda river.

RVNL awarded the construction work of Tunnel 8 to M/s Larsen and Toubro (contractor). Tunnel 8 comprises two tunnel tubes (termed "Upline" and "Downline") which were excavated by single shield TBMs (see next section for technical details). Both TBMs completed their excavations strictly on schedule (Table 1).

Table 1: Timelines and chainages of both TBMs at the Rishikesh-Karnaprayag project.

TBM	**Boring start (planned / actual)**	**Boring completion (planned / actual)**	**Chainage start**	**Chainage end**	**Distance (in Kms)**
TBM Shakti (S-01309A)	28.12.2022 / 17.12.2022	28.4.2025 / 16.4.2022	48+180	58+649	10.469
TBM Shiv (S-01310A)	27.2.2023 / 6.3.2023	30.6.2025 / 30.6.2025	0+880	11+168	10.298

Both TBMs achieved a high performance with monthly advances of up to 710 meters (Table 2). The monthly and cumulative comparison between planned and actual performance is shown in Figure 4.

Table 2: Monthly time percentage utilization of TBM Shakti and TBM Shiv (excluding initial 3 months learning period).

Categories	TBM Shakti (S-01309A) Performance			TBM Shiv (S-01310A) Performance		
	Average	Best	Worst	Average	Best	Worst
Advance	16.47%	21.86%	4.09%	15.48%	26.56%	8.06%
Lining	25.01%	35.21%	7.87%	20.66%	27.86%	9.10%
No Production	58.53%	42.93%	88.4%	63.86%	45.58%	82.84%
Applicable Month	Dec 22 to Apr 25	June 24	Apr 23	Mar 23 to June 25	June 25	Jan 25
Monthly Advance (m)		557	68		710	182
Applicable Chainage	48+180 to 58+649	53+981 to 54+539	48+679 to 48+747	0+880 to 11+168	10+457 to 11+167	8+726 to 8+908

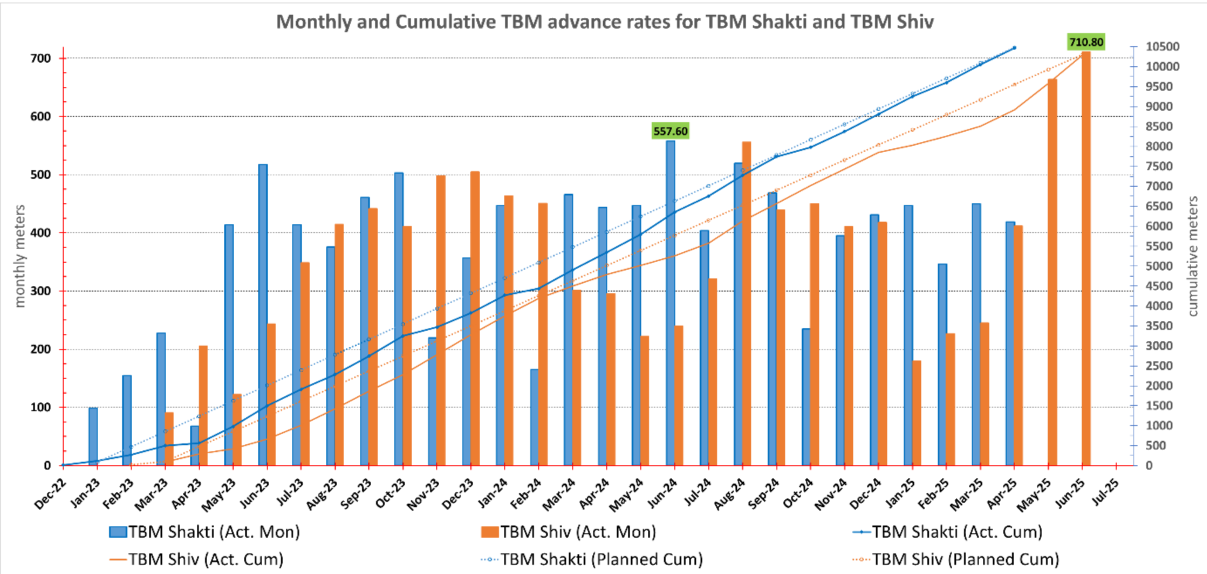

Figure 4: Monthly and Cumulative advance rates for TBM Shakti (S-01309A, Blue) and TBM Shiv (S-01310A, Orange).

Engineering geological investigations for the project were conducted from 2014 to 2018, progressing from desk studies to detailed field and laboratory investigations. Initial studies included literature and imagery reviews followed by 2016 field mapping of lithological and structural features, characterizing rock joints with variable persistence (1–10 m), aperture (0.1–5 mm), and weathering (slight to moderate). In 2018, geotechnical investigations included 15 boreholes (9 along the TBM alignment), geophysical surveys, laboratory testing, and in-situ tests such as permeability, dilatometer, borehole televiewer, and hydro-fracturing.

Tunnel 8 passes through the Lesser Himalayas of the Garhwal region of Uttarakhand. The Lesser Himalaya includes a thrust-bound sector delineated by two tectonic plates i.e. the Main Boundary Thrust to the south and the North Almora thrust (NAT). The rock masses present in the area have undergone a complex history of burial and following exhumation, having been subjected to large stresses with both ductile and brittle deformation representing a fold and thrust tectonic regime. The geology of Tunnel 8 is entirely belonging to low grade metamorphic rocks of Chandpur formation of Jaunsar Group, having a continuous sequence of light and dark grey phyllite with interbedded light grey and purple sandstone and siltstone and presence of quarzitic phyllite. The phyllites are highly crushed and disintegrated because of the NAT. Near the NAT, these rocks are characterized by slickensides, increased discontinuity density dure to crushing, mylonitization and increased weathering. Rock mass classification using RMR (Bieniawski, 1973) and GSI (Hoek and Brown, 1997) divided the TBM tunnels into 12 segments, with 74.51% Class III (fair rock), 23.91% Class IV (poor rock), and 1.58% Class V (very poor rock).

2.2. Tunnel Boring Machines and Void Measuring System

The two TBMs used at the project are identical Herrenknecht (i.e. TBM manufacturer) hard rock single shield TBMs with designations "S-01309A" (Shakti) and "S-01310A" (Shiv). The shield consists of three segments with slightly decreasing diameter (front-, center-, tail-) to achieve an overall conicity. The TBMs are equipped with a Void Measuring System (VMS) which consists of three radially extendable measuring rods, that can measure the gap between the TBMs' shield and the tunnel wall. The three VMS are installed at 3472.5-, 5172.5- and 6872.5 mm distance from the leading edge of the front shield and they are pointing towards the tunnel wall at an angle of 28 degrees clockwise from the center of the crown (tunnel roof), seen in the direction of advance. The VMS rods have a spacing of 1700 mm in between them, which corresponds to the length of one stroke of the TBM (ring width = 1700 mm) (Figure 5). The maximum shield gap (maximal rod extension) that can be measured by the VMS is 250 mm. General technical specifications of the TBMs can be found in Table 3 and a sketch of the main geometrical features is given in Figure 5.

Table 3: Technical specifications of the used TBM-S.

Specification	Value
Cutterhead diameter [m]	9.11
Number of cutters	55
Radius of cutters [mm]	241.3
Total shield length [m]	10.68
Shield outer diameters [m]: front / center / tail	9.05, 9.03, 9.01

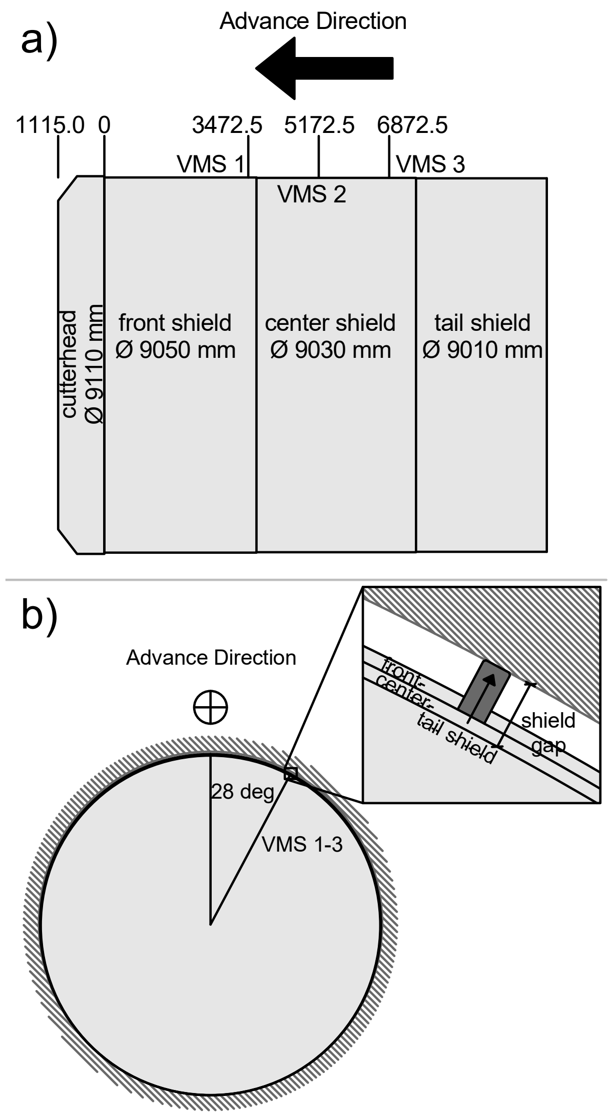

Figure 5: a) sideview of the TBM geometry and positions of the void measuring system (VMS). b) view in advance direction showing the position of the VMS and a detailed view that shows VMS 3 fully extended.

The VMS data (as all TBM operational data) is inherently time based. When the TBM is in a standstill position, all VMS take readings, and hence 3 different tunnel chainages with 1700 mm in between them are measured at the same time. After subsequent strokes, VMS 2 and VMS 3 will measure the shield gap at the same position where previously VMS 1 and VMS 2 took their measurements respectively. This yields three shield gap measurements for the same point and the time difference of the two TBM advances in between, which allows computation of tunnel wall deformation rates [mm/h] (Figure 6a). The geometric effect of the shield conicity (Figure 5) must be considered and the VMS are sensitive with respect to the TBM positioning. If the length of the TBM stroke is deviating from 1700 mm, the VMS will not measure in the same position as before and is thus susceptible to misreadings caused by the tunnel wall roughness (Figure 6b). To reduce the influence of the tunnel wall roughness, only VMS readings were considered where the TBM positioning is within 5 cm of the theoretically correct position (corresponding to the diameter of the tip of the measuring rod).

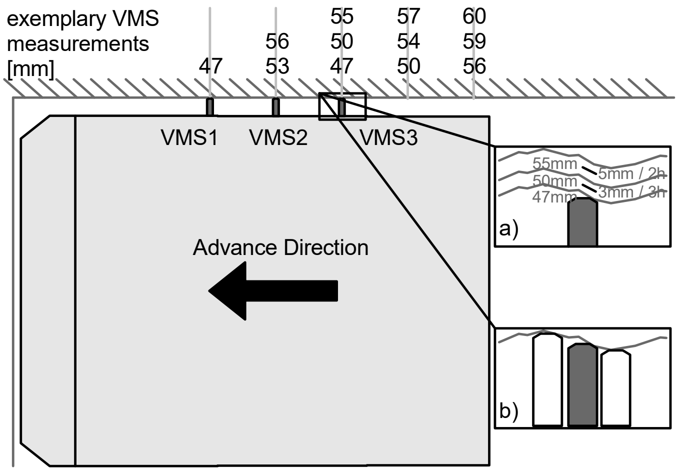

Figure 6: Graphical representation of how tunnel wall deformation rates can be derived from the VMS. a) detailed view with exemplary measurements and time differences between TBM advances of 2 and 3 hours respectively. b) sensitivity of the VMS to tunnel wall roughness.

2.3. Encountered Ground Conditions

Despite all elaborate efforts during both pre-construction and construction phases to identify ground conditions to reduce tunnelling risks, discrepancies between actual and predicted conditions were observed in both tubes. These discrepancies included variations in groundwater inflow into the tunnel, and the presence of shear/fault zones.

During excavation, actual ground conditions were systematically documented through daily geological interpretation reports and site inspections. The TBMs Upline and Downline encountered 21 and 14 water-bearing zones, respectively, with inflows typically ranging from 100–200 L/min, which diminished over time. Although both tunnels exhibited comparable rock mass characteristics, the Upline experienced higher water inflow due to its 300–700 m lead over the Downline, facilitating preferential groundwater drainage. Despite comprehensive pre-construction investigations, discrepancies arose between predicted and observed conditions, notably in groundwater inflow and the occurrence of shear/fault zones.

18 and 11 fault zones were anticipated in the Upline and Downline, respectively, of which 11 and 8 were encountered. Most shear zones extended less than 10 m, except one major zone (~30 m). Shear zones were identified using TBM operational parameters such as torque, total thrust, contact force, penetration rate, and muck analysis. Notably, water-bearing zones at several chainages corresponded closely with pre-construction predictions.

3. TBM Advance Monitoring Methodology

3.1. Data Analysis Framework

For continuous monitoring and analysis of TBM operational data during tunnel construction, a Python-based data analysis framework was developed and iteratively enhanced throughout the project (Figure 7). The implemented system operates in multiple sequential stages: i) TBM operational data generated onsite is transmitted to Herrenknecht servers; ii) the data analysis framework - hosted at NGI - accesses these servers automatically through an application programming interface (API) to fetch the latest available data at intervals of three hours, processes incoming data and performs analyses; iii) the results are uploaded to a SharePoint repository via a second API to make them accessible and viewable directly on-site.

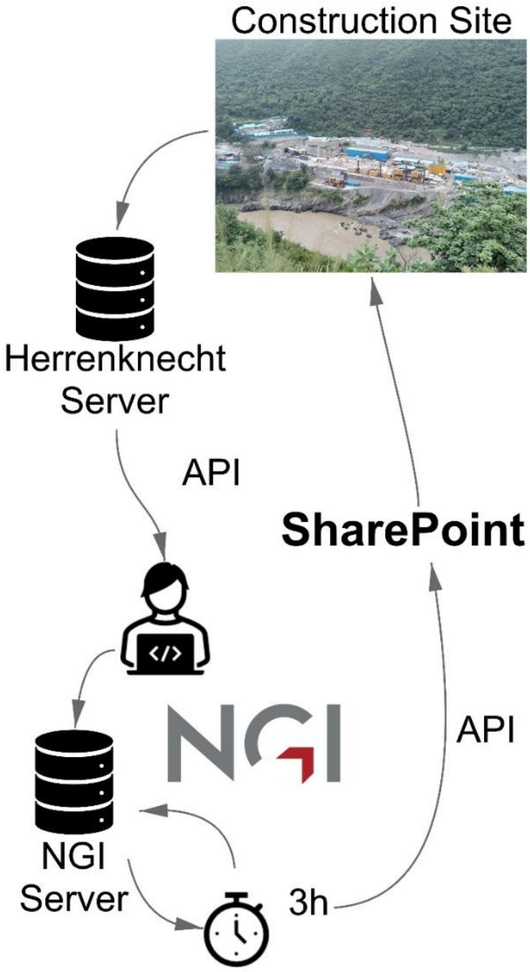

Figure 7: Schematic showing the flow of the information in the developed TBM data analysis framework.

3.2. TBM Operational Data Monitoring

To retrieve a continuous and holistic picture of the excavation conditions on-site advanced TBM data monitoring was done with the above-described framework. While direct TBM parameters such as the total thrust or the cutterhead torque provide valuable operational insights, several additional parameters were computed to retrieve a more nuanced picture of the system behavior (Erharter et al., 2025b). In the Rishikesh-Karnaprayag project, the following parameters were computed:

- **Thrust Force Loss** (F_r): This parameter quantifies the difference between the total thrust force applied by the TBM (F_T) and the effective advance force acting on the cutterhead (F_a) and thus is indicative for the TBM's shield friction (Erharter et al., 2023). F_r is only directly computable for TBMs that separately record both total thrust and advance force.

$$F_r = F_T - F_a \qquad \textit{eq. 1}$$

- **Specific Penetration** (p_s): The specific penetration (Gong and Zhao, 2009) describes the penetration per unit force and is calculated by dividing the penetration per cutterhead rotation (in mm) (p) with F_a (eq. 2).

$$p_s = \frac{p}{F_a} \qquad \textit{eq. 2}$$

- **Specific Excavation Energy** (e_r): Following Teale (1965), this parameter represents the required energy input to excavate one unit volume of rock mass. It can be decomposed into components related to thrust and rotation and especially the latter has shown good correlation with the encountered rock mass conditions. As described by Bergmeister and Reinhold (2017), low specific energy typically correlates with weak rock masses, while high values indicate stronger materials. The rotational specific energy is calculated using eq. 3, where A is the tunnel face area, N the number of cutterhead rotations and T the cutterhead torque:

$$e_r = \left(\frac{2\pi}{A}\right)\left(\frac{NT}{p}\right) \qquad \textit{eq. 3}$$

- **Torque Ratio**: Originally introduced by Radoncic et al. (2014) (see also Erharter et al. (2025b)), the torque ratio compares the measured cutterhead torque (T) to the theoretical torque (M_{th}). It serves as an indicator of ground conditions and is the base for the data driven advance classification now included in the Austrian TBM excavation standard ÖNORM B2203-2 (Austrian Standards, 2023). It is calculated in the simple form according to eq. 4 where F_t is the tangential force acting on the cutters, n_{disk} is the number of cutters, D_{CH} is the cutterhead radius and M_0 is the idle torque required for cutterhead rotation.

$$M_{th} \sim 0.3 * F_t * n_{disk} * D_{CH} + M_0 \qquad \textit{eq. 4}$$

In addition to these parameters the tunnel wall deformations were monitored following the descriptions given in section 2.2. Knowledge about the actual shield gap and especially tunnel wall deformation rates, is hardly ever acquirable in shielded TBMs. The continuous tunnel wall deformation profile acquired in the Rishikesh-Karnaprayag project is seen as unique and can serve as a model for future hard-rock TBM excavations. In addition to the tunnel wall deformation rates, the VMS system also indirectly monitors overbreaks from the tunnel wall when the measuring rods are maxing out, which can be indicative for the rock mass structure.

3.3. Squeezing Risk Monitoring

Analyzing the VMS data, as described in section 2.2, yields a continuous tunnel wall deformation profile with one measurement every 1.7 meters, which is unprecedented in shielded hard rock TBM tunnel construction. As the geology at the project features comparatively soft rocks, overburdens of up to 860 meters and active tectonic stresses (sections 2.1 and 2.3), the risk of squeezing rock mass was deemed to be considerable and a method to estimate the current and continuously evolving squeezing risk was required.

The following input-parameters are used in the developed method for TBM squeezing risk:

a) the tunnel wall deformation rate (r_{def} [mm/h])

b) the length of the shield that can be squeezed in behind the last VMS3 (l_s [m], here l_s = 3.8 m, see Figure 6)
c) the gross TBM advance speed (i.e. excavation speed including standstills) (a_{gross} [m/h])
d) the theoretical size of the shield gap at the end of the shield, given a certain overcut (s [mm]). Note that this must consider i) the shield conicity, ii) the position of the shield, which has a slight offset to the tunnels center.

While the variables a) and b) cannot be influenced during construction, the variables c) and d) can be, by either increasing the gross advance speed (e.g. minimizing maintenance stops) or increasing the shield gap by applying an overcut. It is thus possible to compute the minimum required gross advance speed and / or required overcut to be able to "escape" a deforming tunnel wall and not get squeezed in given a fixed shield length. The required minimum gross advance speed (a_{gross_min} [m/h]) to avoid a closed shield gap can consequently be computed with eq. 5.

$$a_{gross\_min} = \frac{l_s * r_{def}}{s} \qquad \text{eq. 5}$$

This relationship is based on the following assumptions: i) deformations are isotropic and thus displacements are equally distributed around the tunnel periphery, ii) the tunnel wall deformation rate is linear, iii) influences from the neighboring tunnels are not considered, iv) if squeezing occurs, the TBM gets squeezed in from the tail as the tunnel was has had the longest time to deform there. Qualitatively, this equation states that: given a fixed length of the TBM shield and an increasing tunnel wall deformation rate, one must either increase the gross advance speed of the TBM or the size of the shield gap to avoid that the TBM gets stuck.

3.4. Excavation condition prediction

As outlined in Figure 2, the other main task aside from squeezing risk monitoring was to predict the excavation conditions ahead of the TBM to retrieve an early indication of upcoming adverse ground conditions. A supervised ML solution was finally used to predict the excavation condition ahead of the TBM. In accordance with Bozorgzadeh and Feng (2024), however, it is important to justify the use of ML which should go beyond "*some data are available, and we know a class of algorithms for analyzing such data*". The following reasons are given, and thus the ML application in the project complies with the *Problem → Data → Algorithm* paradigm (Bozorgzadeh and Feng, 2024):

i) The notion of an *excavation condition* of a TBM by itself is conceptually challenging as it is neither mechanistically nor physically well defined. While individual phenomena of the TBM's excavation work can be understood with a physical understanding (e.g. a waning cutterhead advance pressure when the TBM enters disturbed – softer – rock mass due to reduced excavation resistance), the totality of the excavation condition is characterized by different emergent phenomena resulting from the interaction of the TBM with the rock mass. Despite this complexity, onsite engineers are still able to determine when the excavation is going well and when it does not, based on experience and "engineering judgement". ML algorithms are thus seen as well suited for this prediction task as their strong generalization capability permits synthetization of experience and "engineering judgement".

ii) TBM excavations constitute one of the data-richest environments in all of geotechnical engineering due to the high amount of data that is recorded by the TBMs. While this by itself already lends itself to ML (Erharter et al., 2019; Erharter and Marcher, 2020), the Rishikesh-Karnaprayag project was particularly well suited, as it had a wealth of data in addition to the TBM operational data, first and foremost, regularly executed exploratory drillings ahead of the TBM with measurement while drilling data (MWD) recording and tunnel seismic surveys that were executed from the TBM.

iii) The last years have seen a massive increase in the further development and application of ML in general (Erharter, 2024) and there is consequently a plethora of algorithms to choose from. For this particular task of sequential tabular data, an ensemble of Random Forest algorithms was chosen as tree-based algorithms still are on-par with more complex ML methods when it comes to this kind of data (Grinsztajn et al., 2022). More detailed descriptions can be found below.

To assign a quantitative label for the notion of "excavation condition", a TBM-operational data driven approach was used to classify the excavation in an objective and transparent manner. The choice was made to use the binary TBM advance classification according to Radoncic et al. (2014) that discriminates either "regular" or "exceptional" excavation. This system is now also implemented in the new Austrian Contractual Standard for underground excavation with TBMs: the ÖNORM B2203-2 (Austrian Standards, 2023). Technicalities of this TBM advance classification system are explained in detail in Erharter et al. (2025b). Aside from its data-driven objectivity, another rational for this choice was the methodological problems from which many other common, index based rock mass classification systems suffer (Erharter et al., 2024; Liu et al., 2025).

Demands for the input data from which the excavation condition could be predicted were that it i) comes from exploration data ahead of the TBM, ii) it contains the desired prediction information in principle and iii) it must have a sufficiently high resolution to show adverse zones of interest. In today's tunnel excavation there are three main investigation measures that fulfill these requirements: exploratory core drilling ahead of the face (not available here), exploratory destructive (percussion) drilling ahead of the face with MWD data collection, and geophysical exploration ahead of the face.

MWD data was the originally preferred input for ML predictions as it can serve as a strong basis for predictions (Hansen et al., 2024). Several attempts were made to use the collected MWD data from the construction site for predictions, but the results were not satisfactory as the data quality was insufficient due to inconsistent and unreconcilable drilling patterns due to multiple different operators. For MWD data to be used successfully for predictions (e.g. as practiced at Scandinavian tunnel construction sites) it must be collected in a highly consistent manner, such as keeping all but one parameter constant, to ensure that a proper signal of the rock mass is retrieved.

Having ruled out MWD data, geophysical investigations ahead of the TBM were the remaining data source. In the Rishikesh-Karnaprayag project, the "*Tunnel Seismic Prediction*" (TSP) system from Amberg Technologies was used (Dickmann and Groschup, 2010). The seismic source in this case was an impact hammer installed on the TBM and geophones were installed in boreholes behind the tunnel face to collect the reflected seismic signals from structures ahead of the tunnel. With geophysical data processing and seismic inversion, the raw data from the geophones is converted to usable information ahead of the tunnel face that can indicate structures and geophysical properties of the geology ahead. The TSP system then yields geophysical parameters like P- or S-wave velocities or Poisson's ratios ahead of the tunnel face as an output. While these parameters are useful for people with a geophysical background, they are not directly relatable to excavation conditions.

Bringing the two systems together, the overall ML concept at the Rishikesh-Karnaprayag project was to use the predicted parameters from the TSP investigation as input to a ML model, and the TBM data-based advance classification as output. This setup combines historical data of already excavated parts of the tunnel and facilitates prediction of strokes that are potentially "exceptional" ahead of the current tunnel face. Through this, the TBM operator can foresee if upcoming strokes of the TBM will be regular or exceptional and hence be able to adapt the TBM excavation accordingly.

The supervised ML approach employed the Random Forest (Breiman, 2001) algorithm, implemented as an ensemble of 50 independent classifiers effectively creating a "*forest of forests*" or "*rank 2*" ensemble. Each Random Forest consisted of 100 decision trees, and the ensemble diversity was achieved through using different random seeds for data sampling and the randomization in the algorithm. As every single random forest yields a deterministic prediction, based on its own interpretation of the training data, the goal of this ensemble of random forests was to retrieve a probabilistic prediction of the expected excavation conditions based on how well the ensemble members agree with each other.

The TSP derived geophysical parameters (P-wave velocity, S-wave velocity, Poisson ratio, static Young's modulus, dynamic Young's modulus, shear modulus and bulk modulus) served as input features while the binary advance classification labels (regular vs. exceptional) based on thresholding torque ratios served as labels. Torque ratio values within the interval {0.65, 1.35} were labeled regular, whilst values outside were considered exceptional. These threshold values were set based on discussions with on-site personal so that they reflected experienced exceptional excavation conditions like overbreaks and other challenges. As the threshold value definition is decisive for the advance classification, it is imperative that this is done in close collaboration with onsite personnel to ensure that it corresponds to the real state of the excavation.

A critical challenge, which is also characteristic of these types of prediction problems, was the inherent class imbalance in the dataset. Regular advances substantially outnumbered exceptional advances. To address this whilst maintaining sensitivity to exceptional conditions, a hybrid resampling strategy was implemented. First, the majority class (regular advances) was under-sampled by removing 20% of the difference in class counts. Subsequently, the minority class was over-sampled using the Synthetic Minority Over-Sampling Technique (SMOTE) (Chawla et al., 2002) which generates synthetic samples by interpolating the features of data within the minority class. This boosts the number of datapoints in the minority class to be the same as the majority class.

The data was then split into a 3:1 stratified train-test split to preserve the class distributions. The test dataset was used for evaluating the predictive capability of the model based on "confusion matrices" normalized by the true class counts. In addition, feature importances were quantified using SHAP (Shapely Additive explanations) values (Lundberg and Lee, 2017), offering insights into which features were steering the predictions. In parallel, a separate ensemble model is trained using the full dataset for forward predictions. To prevent unrealistic changes between consecutive strokes, a smoothing mechanism gradually transitioned from naive predictions (assuming the conditions remain unchanged) and the model prediction in the four coming strokes using the weighting ratios 0.9-0.1, 0.7-0.3, 0.4-0.6 and 0.1-0.9 respectively.

The ML based predictions of advance conditions ahead of the TBM were embedded in the overall data processing framework as described in section 3.1. Due to the integration in the continuously running data processing framework, ensemble models were frequently retrained with a growing dataset thus continuously improving prediction quality.

4. On-site observations and experiences

The continuous monitoring of TBM operational data, described in sections 3.1 and 3.2 permitted retrieving a holistic picture of the state of the construction site remotely. The first row in Figure 8 shows the measured thrust (i.e. the force exerted by the TBMs' thrust cylinders) and the advance force (i.e. the force the cutterhead exerts on the tunnel face). Even though they are no further processed parameters, these are indicative for the frictional loss that occurs as the TBM moves through the tunnel (Erharter et al., 2023). An increasing thrust force, without an increase in advance force thus means that there is increased shield friction, potentially indicative of squeezing conditions or that rock blocks are jammed in the shield gap due to an unstable tunnel wall. The second row shows the computed specific penetration and specific excavation energy. These parameters are negatively correlated with one another, and it furthermore can, for example, be seen how the specific excavation energy is high, when the thrust force is comparatively low and stable, indicating strong rock mass conditions and a stable tunnel wall. Spiking specific penetration is seen as a sign for rock mass of heterogeneous quality as the TBM enters and leaves zones of stronger and weaker rock mass. The third row shows the torque ratio after Radoncic et al. (2014) and threshold values to differentiate regular from exceptional strokes (here 1.35 and 0.65). The thresholds were continuously updated as the excavation progressed which is in line with the ÖNORM B 2203-2 and recent literature (Erharter et al., 2025b). It can be seen that torque ratio spikes above 1.35 align reasonably well with the above-described indicators for weaker, heterogeneous and less stable rock masses, thus further strengthening the holistic picture that is retrieved from the data.

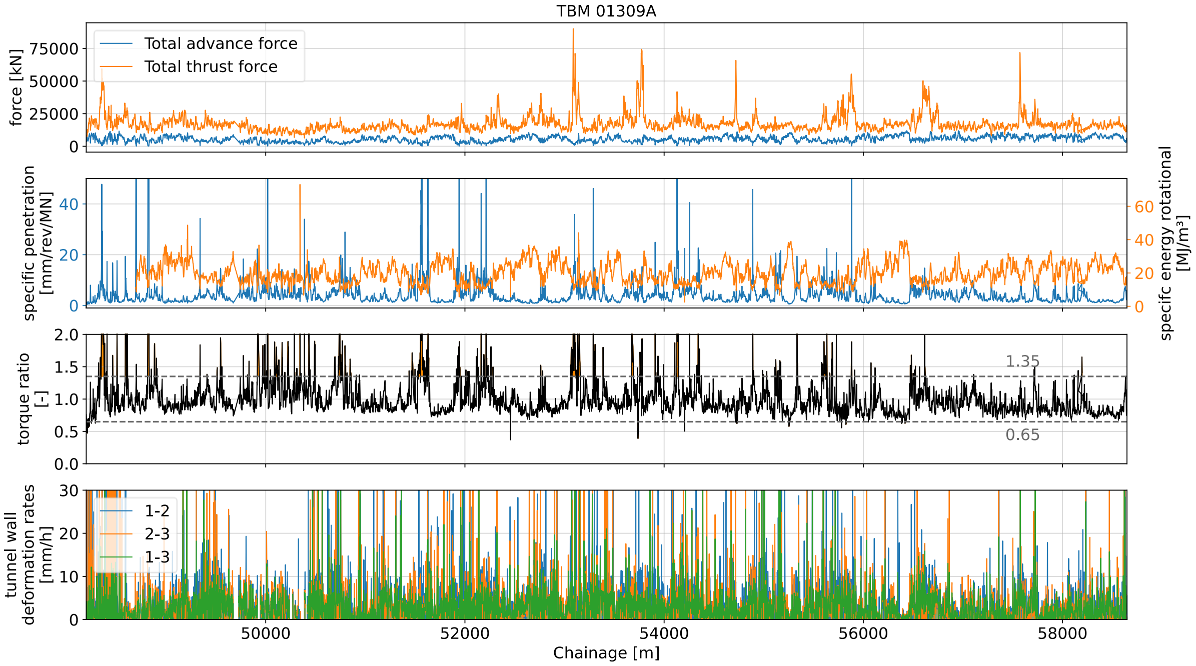

Figure 8: Analyzed TBM operational data for one of the TBMs at the Rishikesh-Karnaprayag project.

The fourth row in Figure 8 shows VMS-based tunnel wall deformation rates as described in section 3.3. Note that there are three deformation rates shown: VMS1 - VMS2, VMS2 - VMS3 and VMS1 - VMS3. For further analyses, always the deformation rate between VMS1 to VMS3 was used as this is seen as the one that best represents the average deformation rate over all three VMS and it was not observed that, for example VMS1 – VMS2 generally has a higher deformation rate than VMS2 - VMS3. In comparison to the other TBM operational data, this signal is noisier, which is seen as related to the mentioned sensitivity to the TBM's position (Figure 6b). Nevertheless, the underlying pattern does correlate with the other above-described indicators that describe the excavation condition and it frequently was observed that elevated deformation rates go along with weaker rock mass conditions.

A detailed view onto one zone where a transition from favorable to less favorable rock mass conditions was encountered by TBM 01309A at about chainage 56450 is shown in Figure 9. As the TBM enters less favorable conditions, it can be seen well how the advance force decreases while the thrust force increases, specific rotational energy decreases, specific energy increases, the torque ratio increases on average and becomes spikey and also the VMS shows increased tunnel wall deformation rates.

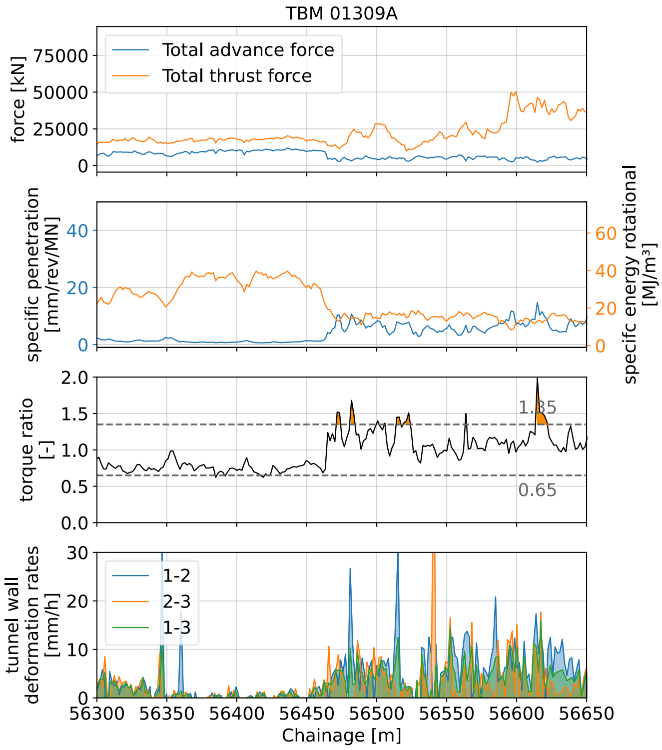

Figure 9: Detail view of the TBM operational data where favorable rock mass conditions are encountered up to ca. chainage 56450 und less favorable ones afterwards.

As described in section 3.3, a special squeezing risk early warning system was developed that utilizes the tunnel wall deformation rates beyond what is shown in Figure 8 and Figure 9. Figure 10 shows one such squeezing risk assessment where the tunnel wall deformation rate as measured by the VMS system is on the x-axis and the gross advance speed (i.e. the TBM advance including standstills in [m/h]) on the y-axis. The diagonal lines that delimit the orange and red sections are computed with eq. 5 and indicate minimum gross advance rates that are required to avoid getting stuck, given a certain tunnel wall deformation rate and the fixed length of the shield. The difference between orange and red is the size of the shield gap, where the former shows the standard shield gap and the latter a widened shield gap due to an applied overcut. The grey dots indicate all past states of the TBM excavation within this diagram and the last 5 strokes are indicated by bold dots, to show how the TBM is doing right now.

If the TBM's current status (bold points) would move into the orange or red shaded area, there would be a risk for the TBM to get stuck due to squeezing rock mass. It can be seen that the vast majority of TBM states are in the safe area and the ones within the orange / red zone can be attributed to outliers and measuring errors. This system of squeezing risk prediction is novel and was developed and used for the first time at the Rishikesh-Karnaprayag project. Even though there never were any severe incidents relatable to squeezing, the system was indicative for the tunnel wall deformation and proved useful to assess the current squeezing risk (on a stroke by stroke basis) in a data-driven way.

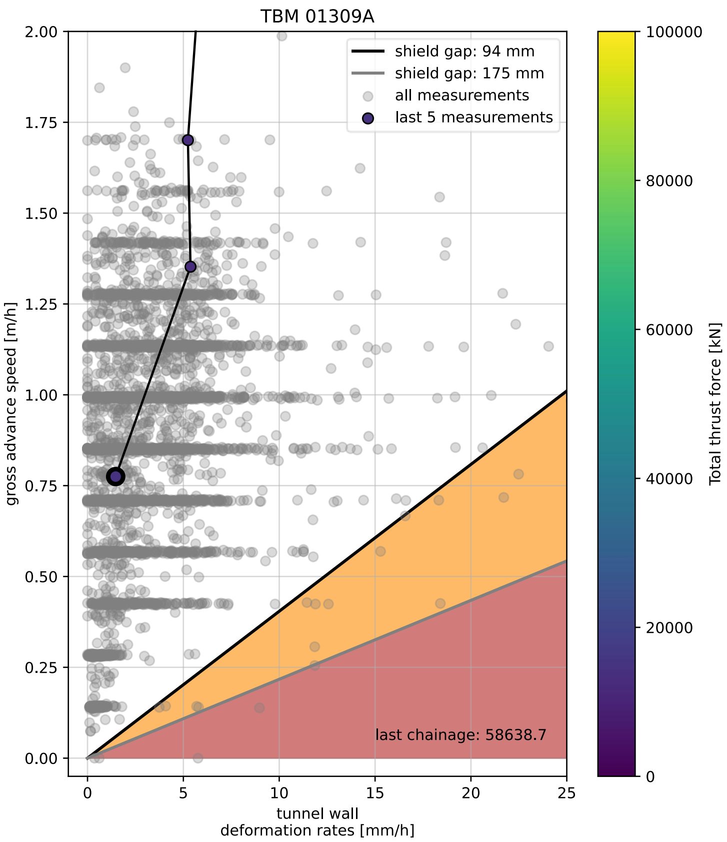

Figure 10: Novel methodology to predict the risk of squeezing in the shield area of a hard rock TBM, that relates the parameters tunnel wall deformation rate, TBM gross advance rate, length of the TBM shield and size of the shield gap. Orange and red areas indicate zones of elevated squeezing risk

The ML and TSP-based predictions of the expected excavation conditions ahead of the TBM yielded a classification of 0 = regular excavation and 1 = exceptional excavation. An exemplary, final prediction ahead of the cutterhead is shown in Figure 11. The upper row of Figure 11 shows the exemplary TSP parameters Vp and Vs. The lower row shows “potentially exceptional advance conditions” ahead of the last available position of the TBM. The prediction goes as far as the TSP reaches ahead of the current position and is consequently subject to change as the TBM advances. The strokes ahead are annotated with their respective stroke numbers. The scale of the y-axis corresponds to 0 (regular stroke) and 1 (exceptional stroke). A predicted stroke that plots above the red line (i.e., 0.5) is potentially exceptional and additional care when excavating this stroke should be applied. The height of the point above the red line gives a certain indication about the model uncertainty with respect to whether or not a stroke can be classified as “regular” or “exceptional”. The model uncertainty is computed based on the ensemble of random forests (i.e. the forest of forests) and, for example, a value of 0.7 for a stroke means that 70% of the random forests predicted that the stroke will be exceptional, but 30% predicted that it will be regular. The 0-1 y-axis labels in the second row were deliberately omitted to avoid overinterpretation on the TBM operators’ side who were the end users of this analysis.

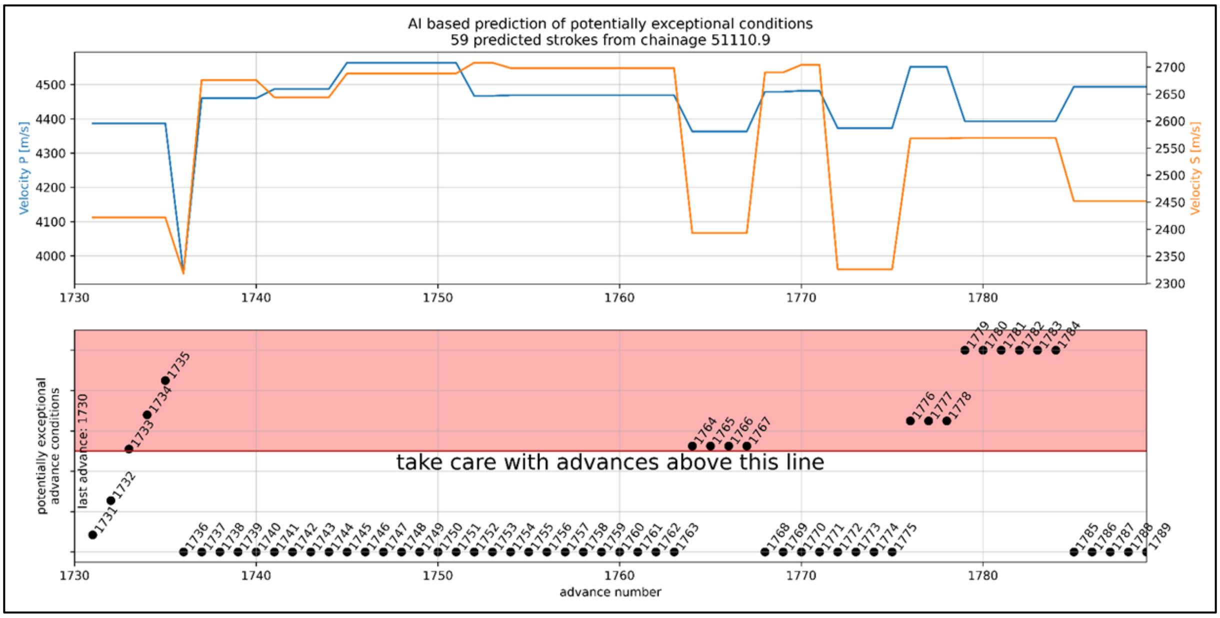

Figure 11: Exemplary output of the ML prediction ahead of the TBM.

5. Discussion

While TBM operational data processing is becoming a standard tool and is done on most construction sites in one way or another, the Rishikesh-Karnaprayag project stands out as its advanced TBMs were equipped with a plethora of sensors that enabled unprecedented possibilities for data analysis. Systems like the VMS proved highly valuable to get an idea about the conditions of the shield gap around the TBM, which is often one of the biggest points of uncertainty in excavations with single- or double shield TBMs. Analyses like those of the VMS data, however, also show that advanced TBM sensors and hardware are required to facilitate comprehensive TBM data monitoring that allows to derive the system behavior from it. Both the software (i.e. the data processing framework) and the hardware (i.e. the TBM) must be sufficiently advanced to allow for advanced analyses.

The TBM operational data processing framework that was developed for the Rishikesh-Karnaprayag project demonstrated how it can be possible to retrieve a holistic impression of the ongoing excavation conditions onsite from a remote office. The chosen update frequency of 3 hours could have been reduced (to, e.g. < 1 hour) but this was not necessary based on the overall excavation progress. In principle, systems like the presented ones could provide analyses and predictions in near-to-real-time, but an hourly frequency is sufficient for today’s excavation performance.

The developed early warning squeezing-risk method is novel and can be used to strengthen risk management at future shielded TBM excavations that employ systems like the given VMS. Several simplifications and assumptions were made in the analyses, such as that tunnel wall deformations are linear over time even though deformations measured in conventional tunneling are known to be decreasing with time (Schubert et al., 2014). The simplification was considered justified as it increases conservatism of the system (considering the potential consequence of an actual squeezing incident) and since one avoids introducing complicated assumptions about the plastic behavior of the rock mass.

In section 3.4 it was described that an initial attempt to use MWD data as the input for the ML predictions was futile due to insufficient data quality. Even if the deployed sensors are of high quality and technologically advanced, the way in which they are operated also has a substantial influence on the final data. If either the primary data collection is flawed due to insufficient sensors, or operational processes disturb the data collection, any further analyses may be futile. Even the most advanced processing techniques are just tools to elicit information that must be inherently hidden in the data. If the original dataset lacks the necessary quality or completeness, no algorithm, however advanced, can compensate for that deficiency. Ultimately, the incentive to provide high quality data often hinges on the contractual boundary conditions.

Nevertheless, in the case of the Rishikesh-Karnaprayag project, the fully data driven ML-prediction system was a success. The use of TSP data as input, and a binary classification of excavation conditions based on the torque ratio as output, has shown to be an efficient and functioning way of predicting advance conditions. Both data sources proved to be well suited for this purpose. The chosen ML approach was algorithmically simple (i.e. no deep ML), but produced sound predictions given the available data. It might have been possible to achieve higher classification performances using different algorithms and systematic hyperparameter optimization frameworks like Optuna (Akiba et al., 2019). The progressively increasing amount of data as the TBMs advanced, however, showed to yield the largest performance increases and thus the focus was rather put on improving the data processing framework than fine-tuning the ML models. With respect to today's ML best-practice recommendations like the one proposed by Erharter et al. (2025a), it can be said that the majority of requirements in the categories ML "*prototyping*" and "*publishing standards*" are fulfilled, except for the "*Dataset and Experiment Control*" which demands full versioning of all past models and data-subsets to ensure full reproducibility of results at any time. This was not done in the project due to practical reasons and time constraints. In principle, however, having version control that goes beyond the used code is highly encouraged for future projects of the kind where eventually decision critical predictions are made.

6. Conclusion and Recommendations

Tunnel construction is an answer to society's need for rapid rail and road connection, pathways for water and energy, and security concerns. Advanced data analysis can substantially aid this endeavor, but it is no "plug and play" process and has requirements with respect to data quantity and quality. Nevertheless, it permits us to get a comprehensive and holistic impression of the ongoing processes at a construction site in general and can also answer very specific questions related to geotechnical risks such as squeezing. By that, a tunnel construction site can be operated more efficiently, safer and more economical as data processing systems like the one presented here help to avoid severe incidents.

The following recommendations can be given for future similar projects:

- All desired data collection endeavors should be included in the construction site contract to ensure that all data is collected with sufficient quality and that no other incentives interfere with data collection quality.
- All information on-site should ideally be collected digitally so that rapid access and sharing of it is possible.
- TBM operational data processing should be done in a code-based manner to ensure efficiency and (internal) reproducibility of results.
- In contrast to conventional consulting jobs, data-driven consulting as presented has a comparatively high work effort in the beginning of the project as a code framework needs to be set up, but this decreases over time once systems are up and running. This needs to be considered on both the client's and consultant's side when projects like this are started.
- While the state-of-the-practice in retrieving TBM operational data today is still through web interfaces and dashboards, accessing data programmatically through an API is a prerequisite for any large scale and especially automatic analyses.
- If ML is ought to be used, the focus should be on the data quantity and quality and not using the most advanced algorithms available.
- If MWD data is to be used for explorative purposes, it must be acquired in a very systematic and controlled manner, so that patterns in the data are representative for the material that is drilled through and not for the drilling operation itself.
- A VMS system can provide vital information for shielded TBM excavations in potentially squeezing rock mass, and more widespread use of VMS and documentation of measurement results is encouraged. This will enable future research related to rock mass behavior and ultimately better management of squeezing risk.

While many of the above-given recommendations are generally applicable for TBM operational data processing, the rock mechanical observations and interpretations of the Rishikesh-Karnaprayag project are confined to hard rock TBM excavations in potentially squeezing rock mass. With all the developments presented in this paper, the Rishikesh-Karnaprayag project stands out as a role model for data-driven hard rock TBM excavation monitoring and tunnel innovation in a practical project.

Code and Data availability

The code and data of the project cannot be shared openly due to confidentiality reasons. The reader is, however, referred to Erharter et al. (2025b) where similar code for TBM data processing is provided in the appendix.

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Sjur Beyer: Conceptualization, Data curation, Formal Analysis, Investigation, Methodology, Software, Visualization, Writing – original draft

Rajinder Bhasin: Funding acquisition, Project administration, Supervision, Writing – review & editing

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