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Article

Advancing TBM Performance: Integrating Shield Friction Analysis and Machine Learning in Geotechnical Engineering

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Abstract: The Ylvie model is a novel method towards transparent Tunnel Boring Machine (TBM) data analysis for tunnel construction. The model innovatively applies machine learning to automate friction loss computation per stroke, enhancing TBM performance prediction in varying geomechanical environments. This research considers the complexities of TBM mechanics, focusing on the Thrust Penetration Gradient (TPG) and shield friction influenced by geological conditions. By integrating operational data analysis with geological exploration, the Ylvie model transcends traditional methodologies, allowing for a comprehensible and specific determination of the friction loss towards more precise penetration rate prediction. The model's capability is validated through comparative analysis with established methods, demonstrating its effectiveness even in challenging hard rock tunneling scenarios. This study marks a significant advancement in TBM performance analysis, suggesting potential for the expanded application and future integration of additional data sources for comprehensive rock mass characterization.

Keywords: TBM tunneling; hard rock TBM; shield friction; performance prediction; torque factor; TBM operational data

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1. Introduction

In tunnel construction, accurately predicting the performance of Tunnel Boring Machines (TBMs) is essential. Due to the complex and often unpredictable nature of the environment, this task has historically been challenging. Traditional predictive models from the Colorado School of Mines (CSM), Gehring and NTNU Trondheim (NTNU) often fall short under varying geological conditions. To improve the accuracy and robustness of evaluating how TBMs perform in different geological settings, this paper proposes a novel approach that combines machine learning with geotechnical engineering. The proposed approach emphasizes the importance of continuous operational data sampling [1–4].

Tunneling records consistently include TBM parameters, such as cutterhead torque and advance force. These parameters provide an accountable imprint that reflects the rock mass conditions encountered during tunneling. Bergmeister et al., Reinhold et al. and Radončić et al. analyzed data using performance parameters like specific energy, specific penetration and torque ratio. The fluctuation of the advance force during a stroke influences these performance parameters [5–7]. The mining process heavily relies on the effective advance force, which is the difference of the applied total thrust minus frictional components. The interpretation of the frictional components is complex due to the various influences between the tunnel face and the physical contact of the TBM with the tunnel walls. The shield friction and backup system movement partially consume the advanced force. As a result, the parameters' ability to precisely represent the rock mass conditions at the tunnel face gets distorted. This phenomenon underlines the need for a more refined approach to evaluate TBM data, considering the complexities introduced by shield friction and its impact on the efficiency of tunneling operations [8,9]. The state of the art reveals that despite continuously recording relevant TBM parameters, such as cutter head torque and advance force during tunneling, existing models must adequately account for the complex interaction between the TBM mechanics and geological conditions. The fluctuation of the advance force during a stroke significantly influences these performance parameters, highlighting the need for a more refined approach to evaluating TBM data, mainly shield friction and its impact on tunneling operations efficiency.

In this context, this paper proposes a novel approach that combines machine learning with geotechnical engineering to improve accuracy and robustness in evaluating TBM performance across different geological settings. This new approach, known as the Ylvie model, combines operational data analysis and geological exploration to help with the accurate prediction of penetration rates and friction loss estimation. The integration of Artificial Intelligence (AI) is a transformative step in TBM performance analysis and prediction. AI-driven algorithms interpret TBM stroke data to unveil previously hidden patterns and correlations. This approach enables the construction of a dual-purpose predictive model adept at forecasting TBM tunneling performance and elucidating the geomechanical properties of the excavated terrain. As the demand for efficient and reliable tunnel construction increases worldwide, the importance of this research direction becomes more evident. It sets a new standard for incorporating AI into complex engineering challenges, paving the way for more precise and efficient TBM operations. This, in turn, contributes to the broader field of geotechnical engineering.

2. Determination of the Friction Force

The Thrust Penetration Gradient (TPG) represents the nonlinear energy demand for the mining process of TBMs. This concept, initially developed by Wild and Weh et al. and adopted by Wilfing, Erharter et al. and Wannenmacher, focuses on understanding the interaction between related mechanical aspects and geotechnical conditions [10–12]. Wilfing simplified Weh et al. and Wild's approach by skipping the lower trust plateau, instead implementing a linear slope for the remaining thrust increase as the torque grows non-linearly. Wilfing attributed the lower thrust plateau to subcritical penetration, which does not affect the mining process. Wilfing acknowledged that there is a 3 mm/rev trigger, regardless of the skewness of the TPG in relation to the geological conditions [10,11,13]. Penetration tests are performed during the start-up of a stroke to adjust parameters like contact pressure or cutterhead rotational speed based on the rock conditions at the site. Results allow tunneling performance prediction and the enhancement or adjustment of existing models. Additionally, the results can be utilized for predicting tunneling performance and improving or adapting existing models. TBM automatically records the TPGs and compares them with given rock properties. To ensure transferability to other projects, the geological prerequisites for penetration tests are, in addition to a face that is as homogeneous, good condition of the discs. Accordingly, a high-quality recording of the rock and rock mass conditions at the face and the tunnel lining is essential [14,15]. TPG plots, as demonstrated in Figure 1, can be employed to showcase the boreability of a specific rock mass using TBMs. At low penetration rates, the thrust force (TF) increases with a superlinear rate. In this range, low penetration rates result in relatively high TF, referred to as subcritical penetration [10]. The energy demand for rock fragmentation necessitates a non-linear TF increase. Gehring characterized the initial loading phase by the formation of a grinding powder in the cutter's kerf [3]. In contrast, beyond the subcritical penetration rate, an additional stress field forms in the surrounding rock, which additionally causes cracks perpendicular to the compressive stress when the tensile strength is reached. Rock chips break out when cracks overlap, causing chipping. The start–stop tests consist of four sections, starting with a cleared stroke. This involves first driving the machine back a short distance from the face and then driving it up "empty"—this relates to the estimation of the static friction [14].

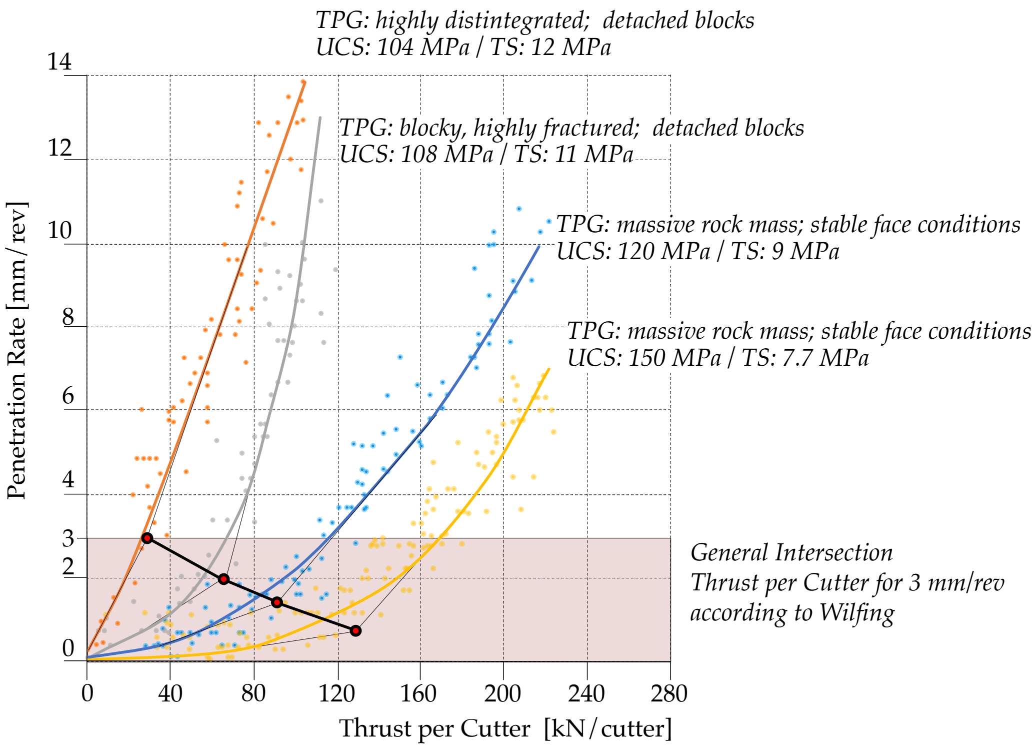

Figure 1. Compilation of the penetration tests carried out on the Koralm Basetunnel for various UCS values and fracturing classes (modified after Wilfing (2016)) [12].

However, the disadvantage of this method is that during such an empty stroke, only the friction of the gauge cutter and shield is measured. During the actual advance, however, the entire cutterhead is mobilized. Gong also showed that the forces between advancing and retracting the machine during the empty stroke differ by a factor of approximately 10 [16]. In addition, the most significant disadvantage of the start–stop tests is that they can also only be carried out selectively during downtimes. The TBM data evaluation comprehensively analyzes the recorded parameters and theoretically determined values. Key indicators among these are the precise penetration rates as outlined by Bergmeister et al. and Reinhold et al. and theoretical torque calculations. The front thrust cylinders of the TBM are significantly impacted by shield friction, which depends on the rock mass quality, the amount of fines in the invert, and the weight and contact area of the cutterhead [5,6].

Shield friction, reflecting the contact area between the shield and the surrounding rock mass, plays a pivotal role in the TBM operations. High friction values, resulting from low rock mass strength or blockages in the annular gap by rock fragments, can substantially influence both the applied TF and the force per cutter. Given that specific project settings and machine types result in different friction values, it is imperative to consider these boundary conditions for a meaningful comparison of prediction models as emphasized by Wilfing [10]. The bandwidth of reported shield friction ranges from 1 up to about 85 percent without transparent allocation to project settings, indicating the shortcomings of current methods for accurately measuring and predicting shield friction [12,17]. The measured TF often needs to reflect the actual force at the cutters due to rock excavation, influenced by factors like friction losses, rigidity, and the force's center of gravity position at the cutterhead. Notably, Türtscher observes that under high initial stress conditions, the effective feed force can be reduced by up to 50 percent. The volatility of various friction loss values highlights the need for a more reliable method of determining friction losses, as the current practice of using idle strokes during penetration tests has shown considerable variation in results, questioning its reliability [18]. Erharter et al.' s study on hard rock TBM tunneling further emphasizes the complexity of assessing shield friction effectively. Their research, which involved specialized shear tests with steel and rock specimens, reveals significant variances in friction coefficients across different lithologies and challenges the expected benefits of using bentonite lubrication. This study highlights the difficulty of accurately assessing shield friction in real-time tunneling conditions as observed by Gong et al. during a series of retracting and pushing tests in a tunnel in Singapore [8,16]. The present paper introduces the Ylvie model, a novel approach to determining friction losses in TBM operations to address these challenges. This model aims to refine the understanding and prediction of shield friction by integrating automated methodologies and insights from the studies above. This model's detailed procedure and implications are explained in greater detail in Section 3. Determining the frictional force (FF) in TBM operations is a multifaceted challenge influenced by various geological, geotechnical, mechanical, and operational factors [19]. In his analysis of frictional losses in TBMs, Türtscher provided a nuanced understanding of the discrepancy between the installed advance force and the effective force exerted on the cutterhead. According to Türtscher, loss ranges between 10 and 25 percent are not uncommon. The lower end of this spectrum, 10 percent, is typically associated with Gripper TBMs, while the higher end, 25 percent, is more common in shielded TBMs. However, Türtscher emphasizes that these Figures do not account for geological–geotechnical factors such as rock strength. He notes that including these factors can escalate the frictional losses to as much as 50 percent. This significant increase underlines the importance of considering machine type and geological conditions in evaluating TBM performance and efficiency [18]. Türtscher's insights highlight the complexities in estimating frictional losses in TBMs, underscoring the need for a comprehensive approach that considers the diverse range of variables influencing TBM operation [18].

Wild's methodology for quantifying friction losses in TBMs is based on the principle ideas of Weh et al. [11] and thus involves a detailed comparison of the contact forces directed along the propulsion path, with the torque measured on a stroke-by-stroke basis. A prototypical illustration of this method is depicted in Figure 2 and can be characterized as follows [13]:

- Within a certain range, the torque remains constant, denoted by a red marker in the Figure.
- A sharp increase in torque is observed beyond a specific threshold.
- Up to a torque level of approximately 1 MN×m, this increase is largely linear, indicated by a green marker.
- Beyond this point, the rate of increase intensifies, reaching a steeper gradient until an upper limit is attained as marked in blue.

The critical task is identifying the intersection between the constant torque section (red) and the linearly increasing range (green). This intersection represents the force necessary to initiate propulsion, overcoming the FF. The mean value of the constant section is calculated and then set equal to the regression function derived from the linearly increasing data points. Following the methodology proposed by Wild, the data are accurately processed to eliminate any outliers, and a comprehensive analysis is conducted, taking into account both the standard deviations of the mean values and the regression curve, to arrive at an accurate and reliable error margin. For the inclined access tunnel of the Nant de Drance HPP excavated by hard rock with a Gripper-TBM, Wild's analysis yielded an average friction loss of about 45 percent [13].

In 2021, Heikal et al. introduced an innovative parameter grounded in empirical data recorded from the Brenner Base Tunnel's exploratory segment between Ahrental and Pfons. This parameter, known as the "theoretical advance force" $F_{N,theo}$, is derived from a retroactive analysis of TBM operational data. The so-called tangential force F_{tang} is calculated based on the torque measured at the cutterhead, the idle torque stroke, and the aggregate of disk cutter radii divided by the total number of cutters as demonstrated in Equation (1) [20]:

$$F_{tang} = (T - T_0) \cdot \sum_{i=1}^{no.c} (r_i) \quad (1)$$

where:

- F_{tang}: Tangential force, also known as rolling force.
- T: Measured torque at the cutterhead.
- T_0: Additional torque.
- $no.c$: Number of cutters.
- r_i: Distance to the center of the cutterhead.

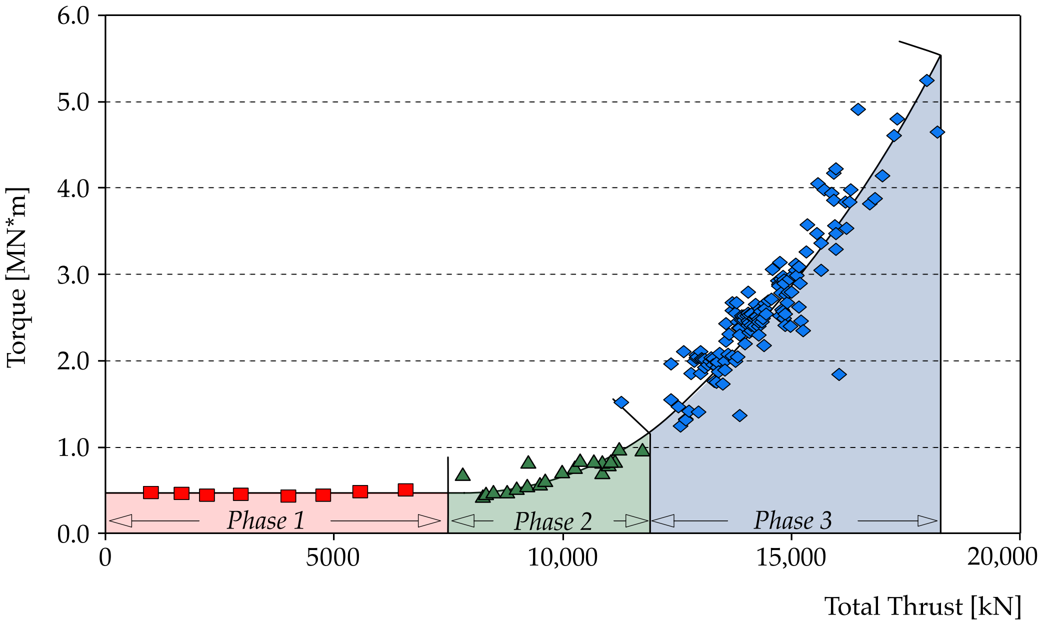

Figure 2. Determination of the friction force according to Wild [13].

The cutting angle (α) is estimated using the penetration depth and the radius of the disc cutter as specified in Equation (2) (compare Figure 3):

$$\alpha = \cos^{-1}\left[\frac{R_{DC} - p}{R_{DC}}\right] \tag{2}$$

where:

- α: Cutting angle;
- R_{DC}: Radius of the cutter;
- p: Penetration depth.

Following this, the normal force (F_n) is ascertained as per Equation (3):

$$F_n = F_{tang} \cdot \left[\tan\left(\frac{\alpha}{2}\right)\right]^{-1} \tag{3}$$

where:

- F_n: Normal force.

Finally, the theoretical contact pressure is deduced from the number of cutters as outlined in Equation (4):

$$F_{N,theo} = no.c \cdot F_n \tag{4}$$

where:

- $F_{N,theo}$: Theoretical advance force.

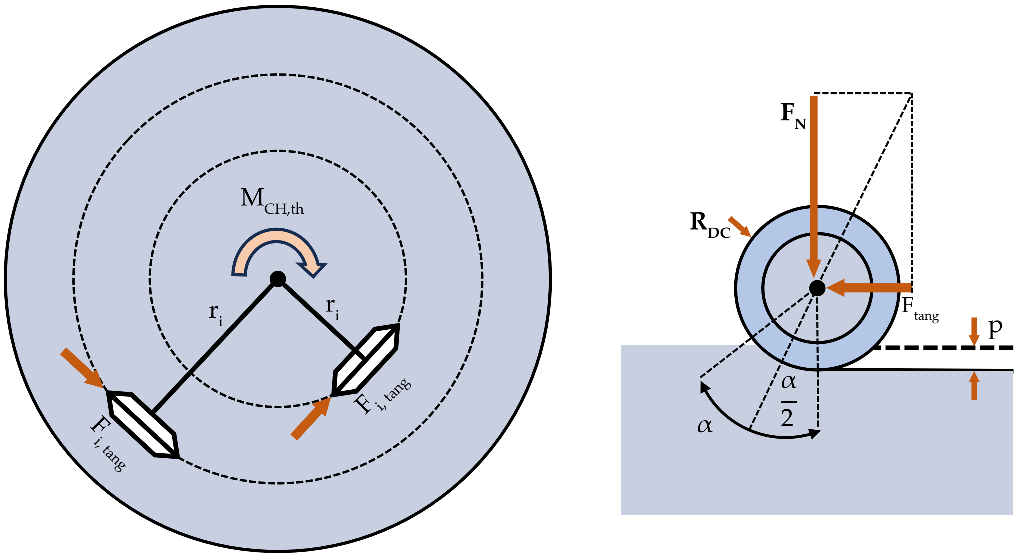

Figure 3. Left: Theoretical cutterhead torque $M_{CH,th}$. **Right**: Relationship between F_{normal}, $d_{penetration}$, r_{cutter}, and $F_{tangential}$ (modified after Radončić et al. [7] and Heikal et al. [20]).

Friction losses are then quantified as the variance between the originally measured TF and the theoretical advance force ($F_{N,theo}$). Nonetheless, this methodology necessitates the determination of the idle torque stroke (T_0), a parameter for which no established method exists. Given its significant dependency on the encountered geological conditions, an automated and precise determination of friction losses remains a complex challenge [20]. Erharter et al. [8] conducted an in-depth analysis of shield friction in TBM operations in hard rock conditions, utilizing theoretical insights and experimental as well as operational data. It included specialized shear tests to determine the friction coefficients in different lithologies and examines the influence of bentonite lubrication. The authors adopted the approach of Heikal et al. [20] in their operational data analysis, using TBM data from the Ulriken tunnel project to estimate shield friction. This comprehensive approach highlights the complexity of accurately assessing shield friction, emphasizing its critical role in TBM performance and efficiency in tunnel construction projects [8].

While existing studies, such as those by Wild [13], Weh et al. [11], and Wilfing [10], have laid a foundational understanding of TPG and its implications for TBM performance, a critical gap remains in the precise and automated calculation of friction losses during TBM operation. This gap is particularly pronounced in the context of varying geological conditions and their complex interplay with TBM mechanics. The studies by Erharter et al. [8] and Heikal et al. [20] have advanced the field by incorporating empirical data and theoretical frameworks to estimate shield friction and advance forces. However, these approaches often require manual adjustments and are limited by their reliance on static parameters, which may not fully capture the dynamic nature of TBM operations. The Ylvie model presented in this paper aims to address these gaps by introducing an automated, data-driven approach to friction loss calculation. This model leverages machine learning algorithms to analyze TBM stroke data, providing a more nuanced understanding of FF and their impact on TBM performance. The Ylvie model novelty lies in its ability to dynamically adjust to operational data, offering a more accurate and real-time analysis of friction losses. This is particularly relevant for challenging hard rock tunneling scenarios, where traditional models often fall short. By bridging these identified knowledge gaps, the Ylvie model not only improves the state of the art in TBM data analysis but also holds significant implications for the broader field of tunnel construction. Its application has the potential to enhance the precision of TBM performance predictions, thereby contributing to more efficient and cost-effective tunneling operations. The relevance of this research is underscored by the growing global demand for reliable tunnel construction methods, making the Ylvie model a timely and valuable contribution to the field.

3. The Ylvie Model

Therefore, this paper presents for the first time the innovative Ylvie model, an advancement in TBM data analysis primarily developed by Schlicke in 2022 and further refined within this paper. This model significantly progresses from earlier methodologies by automating the calculation of friction losses on a stroke-by-stroke basis, a critical improvement over Wild's application. Notably, the model determines the idle torque for each stroke, an enhancement over the generalized assumptions required in previous models [21].

3.1. TBM Data Recording and Pre-Processing

The Ylvie model processes numerous parameters recorded by TBMs, crucial for the detailed analysis of friction losses. These parameters include the following:

- TBM Station Position [m];
- Date and Time of Recording [yyyy:mm:dd] and [hh:mm:ss];
- Stroke Number [-];
- Penetration Rate [mm/rev];
- Measured Thrust Force (TF) [kN];
- Torque at the Drilling Head [MN×m];
- Drilling Head Speed [rpm].

The model converts the vast volumes of raw data into an efficient '.parquet' format, processing the data for subsequent analysis, which includes outlier removal and normalization to ensure data quality [22].

3.2. Computational Methodology for Friction Loss Analysis

The Ylvie model employs a sophisticated computational methodology: [21]

1. Idle Torque Calculation: Aligning with Wild's approach to the TPG, the Ylvie model segments each TBM stroke, starting with analyzing the idle torque phase. This process focuses on identifying phases where the torque levels remain constant despite increasing TF, indicative of the idle stroke. The period where the cutter head is not engaged in an active operation relates to the baseline torque [13]. The Ylvie model employs advanced machine learning algorithms to precisely identify these phases, even in conditions of poor data quality. This process utilizes a sophisticated, iterative approach similar to curve-fitting algorithms. The model effectively identifies the idle torque phase as follows:
    (a) The model begins with a data cleaning phase, initially excluding all instances where either the penetration value or the TF is zero, indicating machine inactivity. It further refines the dataset by eliminating outliers, employing z-scores for outlier detection, given the data's normal distribution. Data points with z-scores above three are removed, ensuring the analysis focuses solely on meaningful instances with positive TF, thereby enhancing the results' accuracy and relevance.
    (b) For a series of strokes denoted by j, the model defines an iterative process for each stroke with iterations indexed by i, setting the step interval i to a constant value of five. In each iteration i for stroke j, an initial TF threshold $\mathrm{TF}_{\mathrm{start},i,j}$ is determined from the maximum value in the TF vector TF_j. The dataset is then iteratively analyzed from $\mathrm{TF}_{\mathrm{start},i,j}$ down to 0, reducing the threshold in predefined step sizes. In every iteration i and stroke j, the dataset is segmented into subsets $S_{i,j}$ based on the TF range $[0, \mathrm{TF}_{\mathrm{start},i,j}]$. A linear relationship between TF (x) and torque (y) is assumed within each subset $S_{i,j}$, modeled by $f(x) = c_{i,j}x + d_{i,j}$, where $c_{i,j}$ and $d_{i,j}$ represent the slope and intercept, respectively. This methodical approach

facilitates a thorough analysis across all strokes, identifying linear relationships within each segmented TF data subset.

(c) In the curve fitting phase, parameters c and d are optimized within defined, physically based constraints to ensure the derived values are feasible and applicable. The parameter d is restricted to positive values but capped below the maximum allowable torque for a stroke, represented as $\text{Torque}_{\max,j}$, mirroring the system's physical constraints. This ensures d signifies a baseline torque within the system's operational limits. The parameter c, defining the slope between TF and torque, is confined to a range that eliminates negative values and includes an upper limit to mitigate excessive torque sensitivity to TF changes, with $0 < c < c_{\max}$. These constraints ensure the curve fitting yields realistic and actionable insights aligned with the system's physical properties and operational conditions.

(d) The threshold $TF_{\text{start,i,j}}$ is dynamically adjusted contingent upon the slope c's sign and the adequacy of data points under the current threshold. Should c manifest as positive or the dataset beneath the current threshold be deemed sufficient, $TF_{\text{start,i,j}}$ is diminished to enhance the granularity of the analysis. In contrast, if c turns negative or the dataset becomes scant, $TF_{\text{start,i,j}}$ is incremented. This iterative calibration continues until a stable mean torque value, denoted as $\tau_{\text{idle},j}$, is determined, epitomizing the idle torque characteristic of the TBM stroke. This $\tau_{\text{idle},j}$ corresponds to "Phase 1" as depicted in Figure 4, representing the initial phase of the TBM operation where the cutterhead is not engaged in excavation.

(e) Upon the completion of the analysis, for strokes identified with data of insufficient quality that hinder accurate idle torque estimation, the model adopts interpolation techniques. It draws on idle torque readings from adjacent strokes, whether preceding or following. This approach ensures the maintenance of continuity and consistency in the idle torque dataset, thereby strengthening the overall robustness of the friction loss analysis.

By adjusting to variations in data quality and employing interpolation when necessary, the Ylvie model ensures that its analysis remains robust and reflective of actual operational conditions, even in the face of data inconsistencies.

2. Frictional Force Calculation: The analysis progresses by approximating the active boring phase, denoted as "Phase 2" in Figure 4, subsequent to determining the idle torque $\tau_{\text{idle},j}$. This phase is characterized by a non-linear relationship between TF and torque, indicating engagement with the material. Data redistribution is an important step in the analysis, designed to neutralize the impact of the time factor. This is essential because "Phase 1" and "Phase 2" of the TBM operation are notably brief compared to "Phase 3" (compare Figure 4). The latter phase typically generates a disproportionately larger number of data points, which could potentially skew the approximation of "Phase 2". To address this, the dataset is segmented based on TF intervals, initiated at $TF_{\text{start,i,j}}$ and incremented by a fixed interval length Δ. For each interval, the mean torque value is calculated, thus redistributing the data to achieve a more balanced representation that accurately reflects the behavior during the active boring phase. This process selectively excludes data points where torque is below $\tau_{\text{idle},j}$. A quadratic function $g_j(x) = a \cdot x_j^2$ is subsequently fitted to this refined dataset to encapsulate the nonlinear increase in torque as a function of TF, characteristic of "Phase 2". The FF, TF_{FF}, is then calculated by solving the equation $g_j(x) - \tau_{\text{idle},j} = 0$. This equation seeks the TF value x_j at which the active boring phase's torque ($g_j(x)$) equals the previously established idle torque ($\tau_{\text{idle},j}$).

3. TPG generation: For the construction of the matrix illustrated in Section 4.2 and Figure 5, characterizing strokes based on TPGs, the original stroke data are adjusted by subtracting the calculated FF. This shift from torque to penetration analysis essentially aims at approximating "Phase 3", facilitating the generation of TPGs (compare

Figure 4). To achieve an optimal fit to the equation $h(x) = ax^2 + bx$, a second round of data redistribution is performed, similar to the procedure described earlier. This step ensures a balanced dataset, crucial for accurately approximating the data points corresponding to this phase.

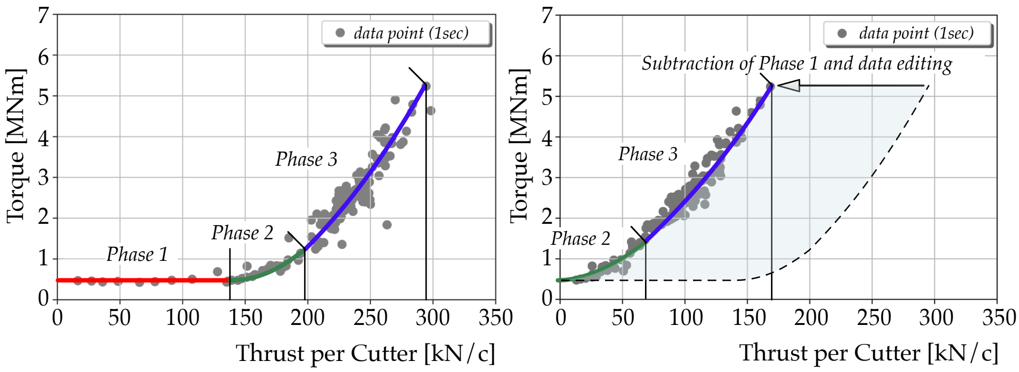

Figure 4. Exemplary stroke before (**left**) and after (**right**) reduction in friction according to the Ylvie model.

4. Applications

4.1. Torque Factor

In this section, the applicability of the Ylvie model for calculating the torque factor as defined by Radončić et al. [7] is investigated:

Radončić et al. provide a relationship between the torque factor f and the system behavior for hard rock shield drives. According to Radončić et al., a torque factor between 0.7 and 0.9 reflects stable ground conditions. If the value falls below this range, increased shield friction is present. In cases where the value exceeds 1.0, fractured material in front of the cutterhead and a potentially higher degree of filling of the cutterhead may cause augmented friction [7].

For the theoretical cutterhead torque calculation, the normal force F_N is determined first. See Equation (5):

$$F_n = \frac{Thrust - 3500}{77} \tag{5}$$

where:

F_n = normal force;
$Thrust$ = measured thrust force;
3500 = friction force measured with push tests;
77 = number of cutters.

Subsequently, the cutting angle α is determined analogously to Equation (2). The tangential force F_{Tang} is then determined as follows:

$$F_{tang} = F_n \cdot \left[\tan\left(\frac{\alpha}{2}\right)\right] \tag{6}$$

where:

F_{tang} = tangential force.

Therefore, the total torque of the cutterhead is the sum of the products of the tangential forces and their respective lever arms on the cutterhead:

$$M_{CH,th} = \sum_{i=1}^{77} (F_{tang,i} \cdot r_i) + M_0 \tag{7}$$

where:

$M_{CH,th}$ = theoretical cutterhead torque;
M_0 = torque caused by inner friction.

Finally, the parameter f can now be determined as follows:

$$f = \frac{M_{CH,real}}{M_{CH,th}} \tag{8}$$

where:

$M_{CH,real}$ = measured cutterhead torque.

The ÖNorm B2203-2 recently adopted the torque ratio—with a fixed FF and idle torque—to delineate regular excavation and additional support measures [23].

The Ylvie model can calculate the torque during idle strokes on a stroke-by-stroke basis. By ÖNorm B2203-2 regulations, it is imperative to establish the idle stroke torque before initiating any tunneling process. This requirement is mandatory to ensure compliance with safety standards and optimal performance. The required torque fluctuates significantly across a project, challenging the idea of a fixed idle stroke torque as shown in the study by Erharter et al. Hence, a dynamic approach like the Ylvie model is proposed for more accurate and adaptable torque factor determination in tunnel construction, ensuring compliance with industry standards and enhancing operational efficiency [8,23].

4.2. Enhanced TPG Matrix Analysis through the Ylvie Model

The Ylvie model's application in constructing a matrix for Thrust Penetration Gradient analysis introduces a revolutionary approach to tunneling performance prediction, particularly in hard rock environments. This matrix, grounded in empirical data from the specific tunnel project investigated in this paper, clusters TPGs based on geological conditions to form a structured system of performance curves. Each cluster within the matrix is defined by a combination of geotechnical parameters—rock strength (Uniaxial Compressive Strength (UCS)) and the rock mass condition, representing rock mass conditions as either 'with minor defects' (trace lengths less than 2/3 of the perimeter) or 'with significant defects' (trace lengths more than 2/3 of the perimeter). The rock strength is segmented into 50 MPa intervals, categorized as per the Hoek–Brown classification. Integrating these geological characteristics with TBM operational parameters, specifically, penetration rates in mm/rev and Ylvie-adjusted TF in kN/cm^2, forms the backbone of this matrix [24,25].

One of the matrix's most innovative applications is its ability to retroactively deduce geological conditions from TBM operational data in areas where direct geological measurements are unavailable. This feature is precious because of the model's capacity to handle non-linear relationships within the data, a capability not present in previous models. The matrix thereby serves as a powerful tool for identifying geological characteristics in tunnel sections that were not directly mapped, allowing for a more comprehensive understanding of the interaction of the TBM with the terrain. Further, the matrix offers predictive capabilities for TBM penetration rates, adding a predictive dimension to the analysis. Aligning clusters with specific TBM operational patterns allows for an anticipatory approach in tunneling projects, where strategies can be adapted based on the expected geological conditions. What distinguishes the Ylvie model's matrix is its unique capability to translate complex, non-linear TBM operational data into meaningful geological insights. This aspect of the model is especially crucial, as it provides unprecedented precision in understanding and predicting the TBM performance in varied geological settings. The strategic importance of this model lies in its ability to fill the gaps in geological knowledge through an advanced analysis of operational data, making it a groundbreaking tool in tunneling and geotechnical engineering. The Ylvie method was recently integrated by Wannenmacher and Schlicke for the analyses of a TBM project in Scandinavia.

Figure 5 shows the relation of TPG with rock mass sub-classes and UCS classes. The TPG flattens with increasing rock strength and decreasing mass fracturing progression. However, there are additional geomechanical characteristics and processes that also influence the TPG, causing a specific scatter and distribution within the different types of rock masses.

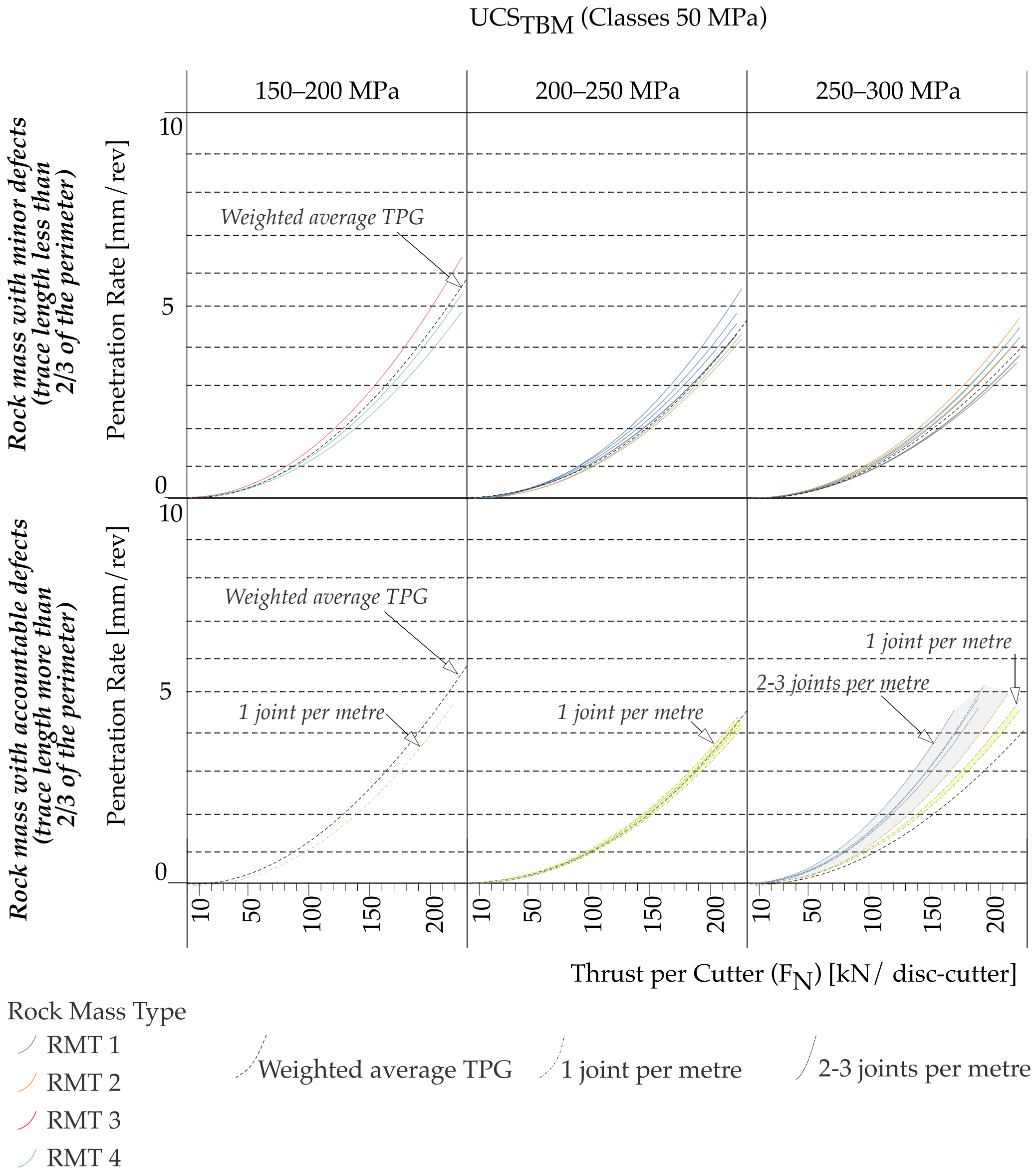

Figure 5. Correlation between Uniaxial Compressive Strength (UCS) and rock mass conditions, categorized into rock mass with minor defects (trace lengths less than 2/3 of the perimeter) and rock mass with significant defects (trace lengths more than 2/3 of the perimeter). The selection of UCS tests for TBM Penetration Rate analyses is based on the methodology of Wannenmacher et al. [26].

5. Model Validation and Comparative Analysis

5.1. Friction Force

The Ylvie model's validation process involved a direct comparison with another established model, specifically the one proposed by Heikal et al., known for its focus on the theoretical advance force. This comparative analysis was crucial in verifying the accuracy and reliability of the Ylvie model, particularly in the context of friction loss estimation. Remarkably, both models yielded nearly identical results in their assessments of a tunnel project. Heikal et al.'s [20] model estimated average friction losses at around 39 percent, while the Ylvie model's estimates hovered around 41 percent. These closely aligned results are graphically represented, substantiating the effectiveness of the Ylvie model in accurately determining friction losses. This alignment validates the Ylvie model and underscores its potential as a reliable tool in TBM performance analysis and tunnel construction projects.

Figure 6 illustrates the nuanced differentiation between the "actual measured TF" and the "calculated TF according to Ylvie/Heikal". The disparity between these values encapsulates the friction force that is meticulously subtracted in both models to yield a more refined estimate of the effective TF exerted on the cutterhead. This distinction is crucial; it highlights the Ylvie model's unique capability to autonomously determine the torque at idle stroke on a stroke-by-stroke basis, offering a more granular and precise analysis of each stroke during TBM operation. This feature significantly enhances the model's precision in estimating friction losses and operational dynamics, further validating the Ylvie model as a reliable tool for TBM performance analysis in tunnel construction projects.

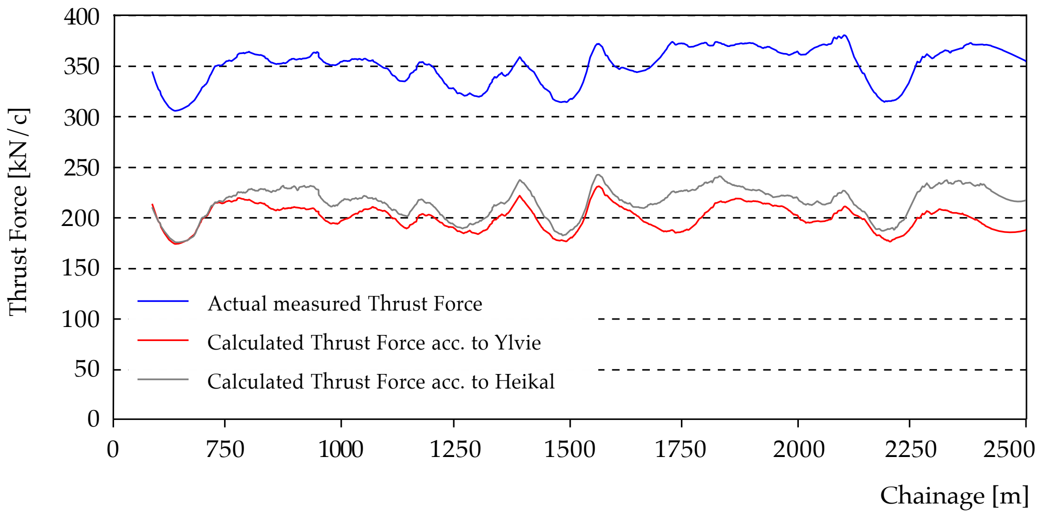

Figure 6. Comparison of Thrust per Cutter values calculated using the model proposed by Heikal et al. [20] and the Ylvie model approach introduced in this paper, with the actual measured values [21].

5.2. Penetration Prediction

In a compelling demonstration of its capabilities, the Ylvie model was applied to predict penetration rates in a tunnel project using data not initially included in the model's matrix. This evaluation was compared to well-established models from CSM, Gehring, and actual tunnel data in a benchmark test. Figure 7 illustrates this comparison.

The evaluation revealed that the Ylvie model outperformed the established Gehring and CSM models, which tended to underestimate penetration rates, particularly in hard rock conditions (>200 MPa) where Gehring's model lacks data. The Ylvie model's enhanced accuracy in penetration prediction is a testament to its sophisticated approach, integrating refined TBM operational data with geological insights. This example underlines the model's potential as a powerful tool for more accurate and reliable TBM performance predictions in diverse tunneling environments.

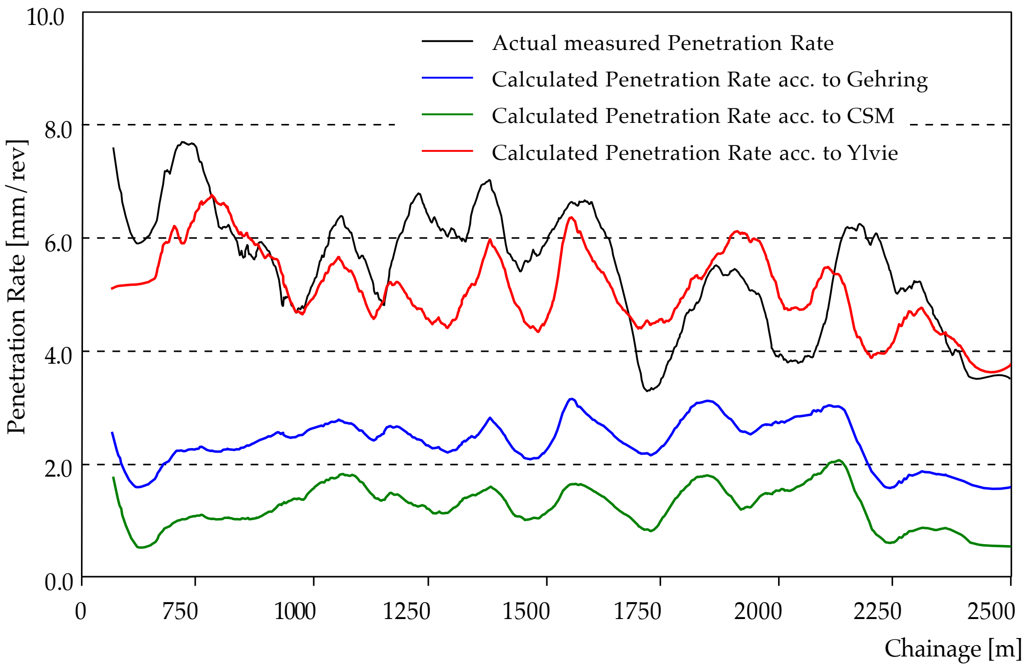

Figure 7. Comparison of penetration rate values calculated using the CSM model, Gehring model, and the matrix approach introduced in this paper, which is based on the Ylvie model, with the actual penetration measurements. The penetration rate consistently corresponds to the Thrust per Cutter as detailed in Figure 6 [21].

6. Discussion

The Ylvie model represents a significant advancement in TBM data analysis, particularly in automating the computation of torque at idle stroke and friction losses on a per-stroke basis, using AI-driven iterative processes. This aligns with the analytical approaches of Heikal et al. [20], demonstrating considerable accuracy and reliability and underscoring the potential of integrating Big Data analytics with geological and technical data for enhanced performance predictions. The model's novel matrix framework offers a unique method for retrospective geological condition assessment based on TBM operational data, contributing to more informed decision-making in tunnel construction projects.

6.1. Limitations

Despite these advancements, the model's applicability is currently limited to hard rock tunneling scenarios using Gripper TBMs, highlighting a need for further data and evaluations to extend its utility across a broader range of tunneling conditions. This limitation underscores the importance of developing more refined methodologies to distinguish between shield friction and face conditions, which may include integrating shield pressure data for a more comprehensive analysis. Addressing these challenges is essential for broadening the model's applicability and enhancing its utility in tunneling operations.

6.2. Future Research

Future research should focus on expanding the model's versatility to accommodate various TBM types and geological settings, enriching the model to consider other critical aspects of TBM operation, such as cutter wear and maintenance, and enhancing the model's predictive capabilities for a more holistic view of TBM performance. This work represents a crucial step in TBM performance analysis, setting the stage for future enhancements in machine-learning applications for rock mass characterization and tunneling optimization.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
CSM	Colorado School of Mines
FF	Frictional Force
RMT	Rock Mass Type
TBM	Tunnel Boring Machine
TF	Thrust Force
TPG	Thrust Penetration Gradient
UCS	Uniaxial Compressive Strength

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