Challenges and Opportunities of Data Driven Advance Classification of Hard Rock TBMs

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Highlights

- TBM operational data is a more objective basis for advance classification
- TBM data analysis can be challenging and requires transparent, computational tools
- Generative adversarial networks are used to provide open, synthetic TBM data
- Recommendations for data driven TBM advance classification are given

Abstract

Tunnel Boring Machines (TBMs) have revolutionized tunneling industry and are currently the dominant method of tunneling in all ground types including soil and rock. Traditional approaches to TBM advance classification, however, rely heavily on subjective assessments by onsite personnel, which are often hampered by limited access to the excavation face and discontinuous observation intervals. This paper elaborates on the shift towards data-driven methodologies for TBM advance classification, which leverage continuously recorded TBM operational data to provide a more objective, transparent, and reproducible assessment of excavation conditions. We discuss the challenges associated with TBM data analysis, including the need for computational tools capable of disentangling complex influences such as rock mass conditions, TBM machinery, and operational logistics. To support the advancement of this field, we provide synthetic TBM datasets generated by generative adversarial networks (GANs), which can be utilized to circumvent issues related to data confidentiality and Python tools to facilitate adoption by practitioners. GAN based data sets used in this analysis have been developed based on the actual field measurements made on TBMs and hence are authentic and reliable for such applications. We also provide practical recommendations for implementing data-driven TBM advance classification, using the torque ratio as a reliable representative of machine penetration rate. This work underscores the potential of data-driven approaches to enhance TBM tunneling efficiency while addressing the technical challenges that accompany their implementation.

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Keywords: TBM tunnelling, Hard Rock TBM, TBM performance analysis, advance classification, data preprocessing, data driven classification

1. Introduction

Excavation by tunnel boring machine (TBM) has become the method of choice for driving longer tunnels in more or less homogeneous rock mass conditions (Maidl et al., 2008). As in all tunnel excavations, TBM tunnelling requires continuous characterization and classification of the system behavior which refers to the behavior of the rock mass in combination with the chosen construction and excavation measures (ÖGG, 2023). This approach is attractive and to some extent necessary to i) react to variable ground conditions with respect to the TBM operation (e.g., careful advance in adverse ground conditions), ii) adjust the tunnel support according to the encountered ground conditions (e.g. using standard vs. heavy ground support) and iii) have a more consistent basis for compensation of the contractor depending on the established measurement and payment in various ground classes within the overall contractual framework. The usual way of acquiring these system behavior classifications is to follow geomechanical design guidelines as for example given by ÖGG (2023) or to use one of many existing rock mass classification schemes (Erharter et al., 2023b) in combination with the project specific contractual framework.

These "classical" approaches towards system behavior classification suffer from the shortcomings of subjective perceptions of onsite personal which need to assess the current state of the excavation using available sensory systems: natural (visual, smell, touch), instrumental. While this is less of a challenge in conventional drill and blast tunnelling due to open access to the tunnel face and -walls, this approach is particularly problematic in TBM tunnelling where the observability of the rock mass conditions is largely obstructed due to the TBM machinery thus rendering sensory perceptions even more unreliable. Additionally, "classical" excavation condition assessments, that are mostly done once per day, are in conflict with high performance TBM excavation for two more reasons: i) high excavation performance (up to over 30 meters per day) is achievable today, but physical inspection visits to the cutterhead are time consuming and an obstacle to excavation performance, ii) large observational gaps occur if a high excavation performance is achieved but the excavation conditions are only characterized once per day.

To alleviate the downsides of classical system behavior determination, increasing focus is directed onto deriving the system behavior from the TBM operational data which modern TBMs often record on 1 Hz or sample per second frequency. The recorded TBM operational parameters are a function of: i) the encountered rock mass conditions, ii) the TBM configuration and iii) the working processes and logistics (Thuro, 2002); (Figure 1).

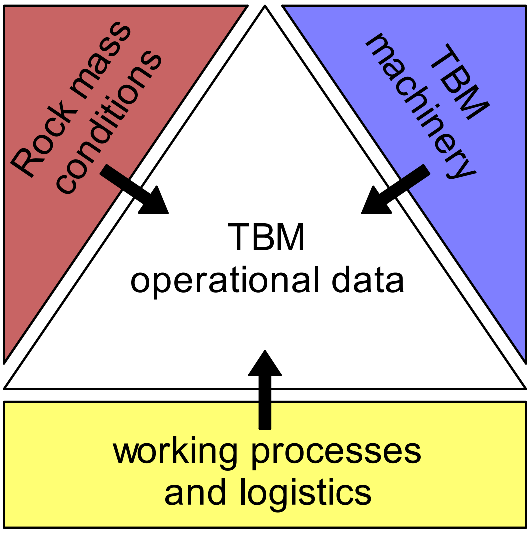

Figure 1: Main influences on the TBM operational data (modified after Thuro (2002)).

While this combination of different influences makes it challenging to interpret individual signals (e.g., if one is only interested in the rock mass conditions), it makes the TBM operational data well suited as a parameter for identifying the system behavior. Advance classification based on TBM operational data has the following advantages over classical classification: i) data-driven classifications are comprehensible and reproducible and not based on black-box, engineering judgement; ii) the TBM operational data is recorded in any case and thus the excavation performance is not disrupted by the face inspection and classification effort; iii) the TBM operational data provides a continuous and uninterrupted record of the excavation conditions and thus allows for continuous advance classification. It must be noted, however, that TBM advance classification based on analysis of operational data is not necessarily fully objective, as also the data driven classification process may require manual interventions.

Recognizing these advantages, recent studies have been completed to look into data-driven advance classification, also utilizing machine learning technology for this purpose (e.g. Erharter and Marcher (2020); Liu et al. (2020); Liu et al. (2021); Xue et al. (2023)). Early indications of the possibility to use the TBM operational parameters to identify the ground conditions and to recognize the possibility of high ground convergence in weaker rock masses based on cutterhead torque was in early 2000's when some of the shielded machines working in weak rock masses had to deal with long delays due to machine entrapment. These studies showed that low torque reading with high thrust was a good indication of encountering weak formations being ahead and to alert the operators to be ready for possibility of high ground convergence, which could be avoided by faster tunneling in related formations (Farrokh and Rostami, 2008, 2009). While these approaches pushed the research front, the recently published Austrian contractual standard ÖNORM B 2203-2: "Underground Works – Works Contract – Part 2: Continuous Driving" (Österreichisches Normungsinstitut, 2023), seems to be the first attempt towards implementing data-driven advance classification in engineering practice. The data-driven advance classification scheme of the ÖNORM B 2203-2 is based on the "torque ratio" which is a parameter computed from TBM operational data, that was first introduced by Radoncic et al. (2014) in the course of the Koralm base tunnel project. Since then, the parameter was incorporated into a contractual framework that was developed since 2016 with intermediate reports provided by Bach et al. (2018), Radončić et al. (2019) and Holzer et al. (2021). The torque ratio is used for demonstration in this paper, although other parameters for advance classification are possible as well.

The authors of this paper see this new standard as a necessary step towards comprehensible and transparent TBM advance classification. However, new systems like this come along with challenges and data driven advance classification requires that the geotechnical engineer onsite has to deal with unprecedented data analyses problems outside of their usual domain of expertise. This paper therefore highlights challenges and opportunities of data-driven advance classification that cannot be covered in the practical framework of a contractual standard. As an additional aid for practitioners, we provide TBM operational data in the data availability section of this paper, including examples for how to compute the torque ratio based advance classification using Python. To avoid the problem of confidentiality that comes with real data sets, the provided data was synthesized using artificial neural networks that were trained to mimic patterns of real TBM operational data while creating original and new data that is unrelated to real construction sites (Unterlass et al., 2023).

Methodological explanations on how the torque ratio is computed and how realistic TBM operational data for three construction sites is synthesized is provided in section 2. A workflow for processing TBM operational data for advance classification is then presented in section 3. The data processing is discussed in section 4 and the paper finishes with a conclusion and recommendations for the TBM operational data based advance classification in practice in section 5. Synthetic TBM datasets and Python codes are provided in the paper's data availability section and links to files in the code repository are also offered (see Github repository: FOLDER, FILENAME, FILETYPE).

2. Methodology

2.1. Computation of torque ratio

The definition of the torque ratio has been introduced by the need for a dimensionless variable allowing insight into the basic coupling between the main operational parameters of a hard rock TBM. Required input variables are a TBM's penetration rate (i.e. advance length per rotation of the cutterhead [mm/rot]), cutterhead thrust [kN], cutterhead torque [kNm] and disc cutter layout on the cutterhead. They are coupled by the simple fact that the cutterhead is constantly rotating, and therefore the resulting disc cutters' cutting force is acting in both axial (against the direction of the advance) and tangential (against the cutterhead rotation) direction. The cutterhead thrust is the sum of all normal forces of the cutters, and the cutterhead torque is the sum of the moment caused by all cutters as a result of the rolling force. The ratio between the measured cutterhead torque and the theoretical cutterhead torque therefore gives an indication whether or not all disc cutters are in contact with the face. If the measured torque is substantially different than the computed one, it can indicate that either not all cutters are in contact with the face (which can point to possibility of a partial face failure), or an additional frictional resistance is mobilized (for instance: by having debris and fragments between the cutterhead and the face).

The torque applied on the cutterhead is either directly measured and recorded in the TBM operational data or can be calculated from i) the recorded electric current and/or power applied to the electric drive of the cutterhead to which it is linearly coupled or ii) from the pressure and flow of the lines for a hydraulic drive system. The exerted torque (M) is given by dividing the power (P) with the rotational speed of the cutterhead (ω) (eq. 1):

$$M = \frac{P}{\omega} \qquad \text{eq. 1}$$

The theoretical torque is computed applying the relationships published by Rostami (1997, 2013) or Rostami and Ozdemir (1993) in their simplified form for calculation of normal and rolling forces. The cutting angle (α), defining the theoretical contact area between the rock and the disc cutter, is a function of penetration (p) and the disc cutter radius (R_{DC}) as in eq. 2. The general setting of the disc cutter cutting condition is shown in Figure 2:

$$\alpha = arccos(\frac{R_{DC} - p}{R_{DC}}) \qquad \text{eq. 2}$$

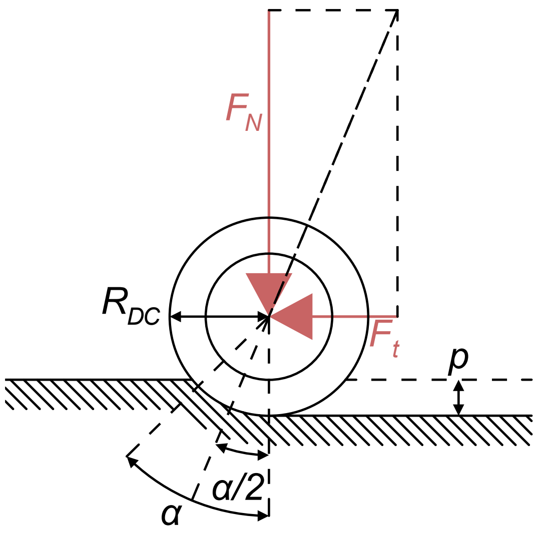

Figure 2: Longitudinal section of the disc cutter in operation.

The applied disc cutter thrust (F_N) is determined by dividing the total cutterhead thrust (F_{CH}) by the number of installed cutters (n_{disk}) (eq. 3):

$$F_N = \frac{F_{CH}}{n_{disk}} \qquad \text{eq. 3}$$

It is assumed that the cutter force resultant is bisecting the contact area symmetrically, thus allowing calculation of the tangential (rolling) force component (F_t) from F_N and α (eq. 4):

$$F_t = tan(\frac{\alpha}{2}) * F_N \qquad \text{eq. 4}$$

The theoretical torque (M_{th}) is then obtained by summing up the product of the individual cutters' tangential forces (F_{ti}) with the respective distance to the cutterhead centre (R_i) (eq. 5) or M_{th} can be approximated with a simplified equation that includes the cutterhead diameter (D_{CH}) (eq. 6).

$$M_{th} = \sum_{i=1}^{n} F_{ti} * R_i \qquad \text{eq. 5}$$

$$M_{th} \sim 0.3 * F_t * n_{disc} * D_{CH} \qquad \text{eq. 6}$$

The corresponding geometrical relationship is presented in Figure 3.

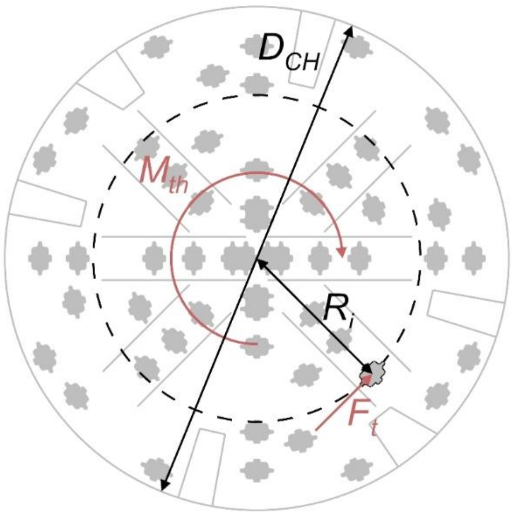

Figure 3: Theoretical cutterhead torque and the disc cutter layout on the cutterhead.

The torque ratio (TR) is finally determined as the ratio between the real cutterhead torque M and the theoretical torque M_{th} under consideration of the frictional loss M_0 (torque required to overcome the internal machine friction and start the cutterhead rotations) (eq. 7):

$$TR = \frac{M}{M_{th} + M_0} \qquad \text{eq. 7}$$

The value of M_0 has been found to equal approximately 250 kNm on large diameter machines but it is recommended to determine it from the machine data at the beginning of strokes following longer maintenance shifts where the cutterhead was not in contact with the tunnel face. In other words, the torque used to rotate the cutterhead when it is not engaged with the face (at zero advance force).

The validation of the presented relationship has been performed on different international projects, and it has been shown that the relationship works as an indicator of the face stability for all TBM types with a hard rock cutterhead (Bach et al., 2018). For example, the longitudinal section of a tunnel through hard, crystalline rock mass with superimposed TBM data and the torque ratio is shown in Figure 4. Note how the torque ratio corresponds closely to each encountered and documented strongly jointed rock mass zones in the geological profile. (see Github repository: src, DATA_XX_library.py, Python file)

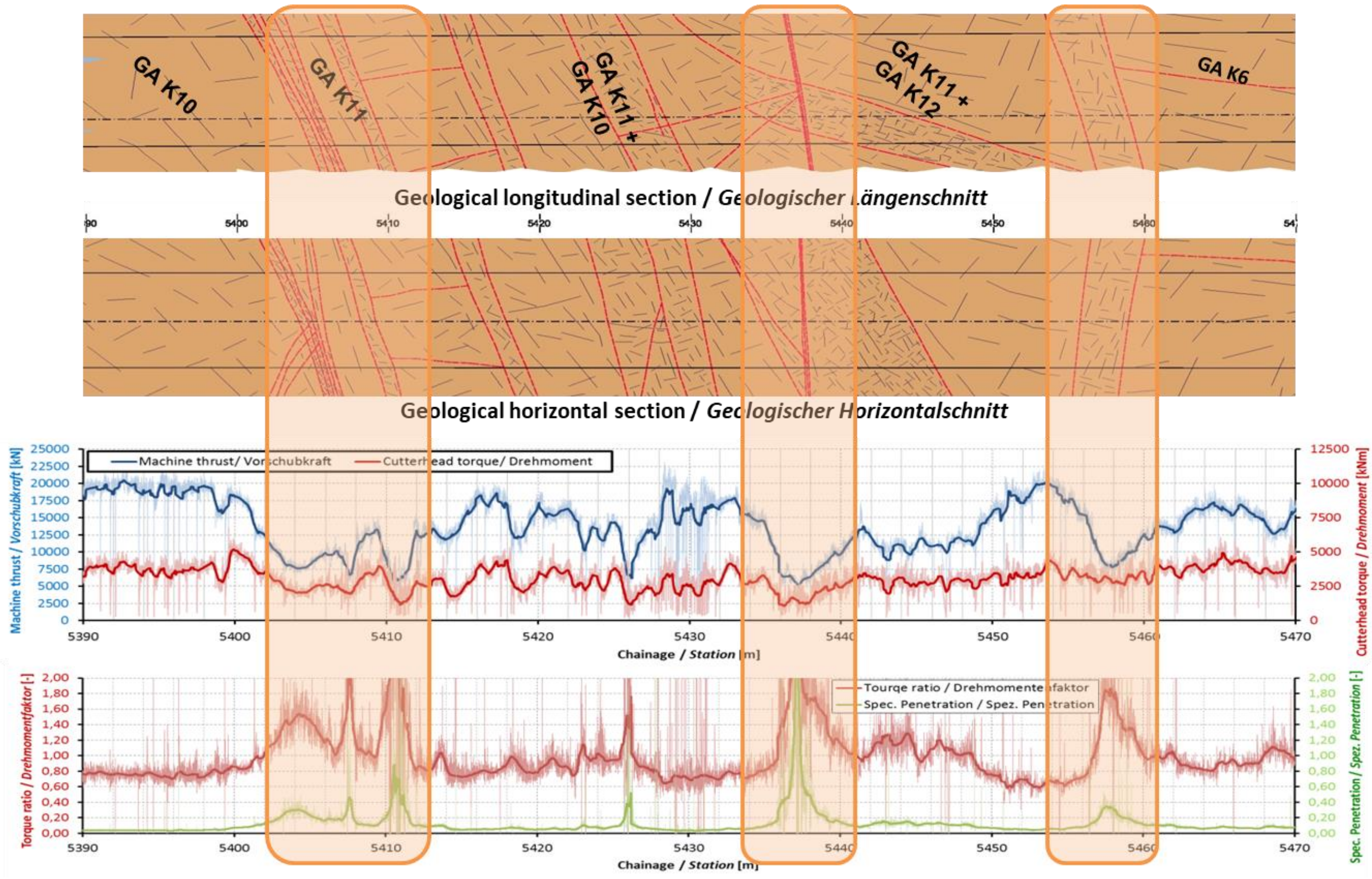

Figure 4: Longitudinal section, operational parameters and the torque ratio of hard-rock, double shield advance. Taken from Radoncic et al. (2014).

2.1.1. TBM specific considerations

The calculation of the cutterhead thrust is machine type specific and therefore thorough consideration of the entire system must be taken into account. In case of double-shield TBMs, the main thrust cylinders are located between the front and the gripper shield. The measured thrust contains the friction of the front shield and the net cutterhead thrust, and the shield friction must be regularly determined by test strokes. Additional information on the rock mass loading of the shield is presented by analyzing the forces required to move the gripper shield during regripping, therefore giving direction information on possible presence of debris in the annular gap and/or onset of squeezing pressure building up (Hasanpour et al., 2014; Hasanpour et al., 2015; Hasanpour et al., 2020).

Similar logic applies to gripper TBMs, where the applied thrust equals the sum of the gripper shield friction and cutterhead thrust. Additional information can be retrieved by measuring the pressure development in the shield segments (if present), therefore receiving direction indication on the interaction between the rock mass extrados and the shield.

Single shield TBMs have usually actuated cutterheads and can measure the applied cutterhead thrust directly by monitoring articulation joint cylinders hydraulic pressure. The main thrust cylinders act on the entire shield. If these force measurements are used, one must consider that the total thrust is in this case the sum of shield friction, cutterhead thrust and the towing force for the backup trailer. More information on TBM shield friction for all TBM types can be found in Erharter et al. (2023a).

2.2. Generation of artificial TBM data

In geotechnical engineering, confidentiality constrains possibilities for the use of real datasets. To bypass this problem, a generative adversarial network (GAN) (Goodfellow et al., 2014) based approach of generating artificial TBM operational data was adopted. In accordance with Unterlass et al. (2023), the generated data is associated with the following dualistic requirements: i) the data must be sufficiently dissimilar from the original data, in order not to create confidentiality issues – i.e. the “demand for originality”; ii) it must show the same patterns and follow the same rules as the original data, in order to be used as if it was from a real TBM data – i.e. the “demand for conformity”.

GANs belong to the group of generative classifiers (Ng and Jordan, 2001), and are based on a game theory scenarios in which two artificial neural networks compete against each other. The generator network directly produces (artificial) samples from random noise input variables and calculated parameters (i.e. weights). Its adversary, the discriminator, attempts to distinguish between samples taken from the training data (i.e. real data) and samples from the generator (i.e. generated data). The discriminator network outputs a probability value, indicating if the sample presented is real (i.e. taken from the training data) or fake (i.e. generated data). During training of the GAN, the generator is continuously trying to fool the discriminator by generating ever more realistic data, whereas the discriminator is constantly improving in differentiating between fake and real samples. At convergence, meaning the point in training, where the generator’s samples are indistinguishable from real data, the generator network has successfully learned to accurately reproduce the underlying data distribution, mimicking that of the real-world data.

GAN training and examination of the generated data can be difficult in practice (Goodfellow et al., 2020). However, a previous study (Unterlass et al., 2023) has shown that, particularly Wasserstein GANs (Arjovsky et al., 2017) provide promising results when given the task to specifically generate TBM operational data.

Thorough evaluation is necessary to check whether the requirements placed on the artificial data are met. As proposed in Asre and Anwar (2022), dimensionality reduction algorithms (e.g. t-SNE (van der Maaten and Hinton, 2008) and PCA (Pearson, 1901)) allow for visual inspection if the artificial data is showing the same patterns and following the same trends as the real data. The demand for originality, validating the preservation of privacy was assessed by using the distance to closest record method (Park et al., 2018). Here, the Euclidean distance between any artificial record and its closest corresponding neighbor from the real data is calculated and evaluated.

2.2.1. Generated datasets

By applying the Wasserstein-GAN, three sets of artificial but realistic TBM operational data were generated. The generated datasets are based on real TBM operational data from three different construction sites including two gripper TBM excavations (here named TBM A and TBM C) and one double shield TBM excavation (here named TBM B). (see Github repository: data, "TBM_X_0_synthetic_raw" (replace X with A, B, C for each TBM), parquet files).

By sampling from the trained generator model, i.e. feeding it with random noise, we can generate infinite sequences of artificial TBM data. The data sequences generated in this way have a vector length of 4096 consistent data points (i.e. observations) per sequence. This sequence-length is predetermined by the internal architecture of the GAN's artificial neural networks, whereas longer sequence-lengths would significantly increase the demand for computing power. Presenting the GAN model architecture is outside the scope of this paper, but the full source code, including the neural network architecture is given in the src folder of the Github repository in the data availability section of the paper: i.e. the Python scripts starting with "WGAN_". Depending on the average datapoint-spacing in the training data, (e.g. 0.05 m for TBM_A), one sequence of artificial data comprises a continuous section of *spacing * sequence-length* tunnelmeters (i.e. 0.05 * 4096 = 204.8 m for TBM_A), however, it must be noted that the tunnel length / chainage for each datapoint was back-calculated based on the artificial penetration rate and a constant number of cutterhead rotations (see below).

Figure 5 demonstrates that both the "demand for originality" and the "demand for conformity" are fulfilled in the generated dataset. Rows 1 to 3 show randomly selected artificial sequences of the cutterhead torque [MNm] in the background (black) and the most similar corresponding real TBM data sequence in the foreground (white). Row 4 shows the results of the t-SNE dimensionality reduction for these sequence pairs. From Figure 5 it can be observed that both sequences (real and artificial) plot in the same range, show the same patterns and follow the same trends without being copies.

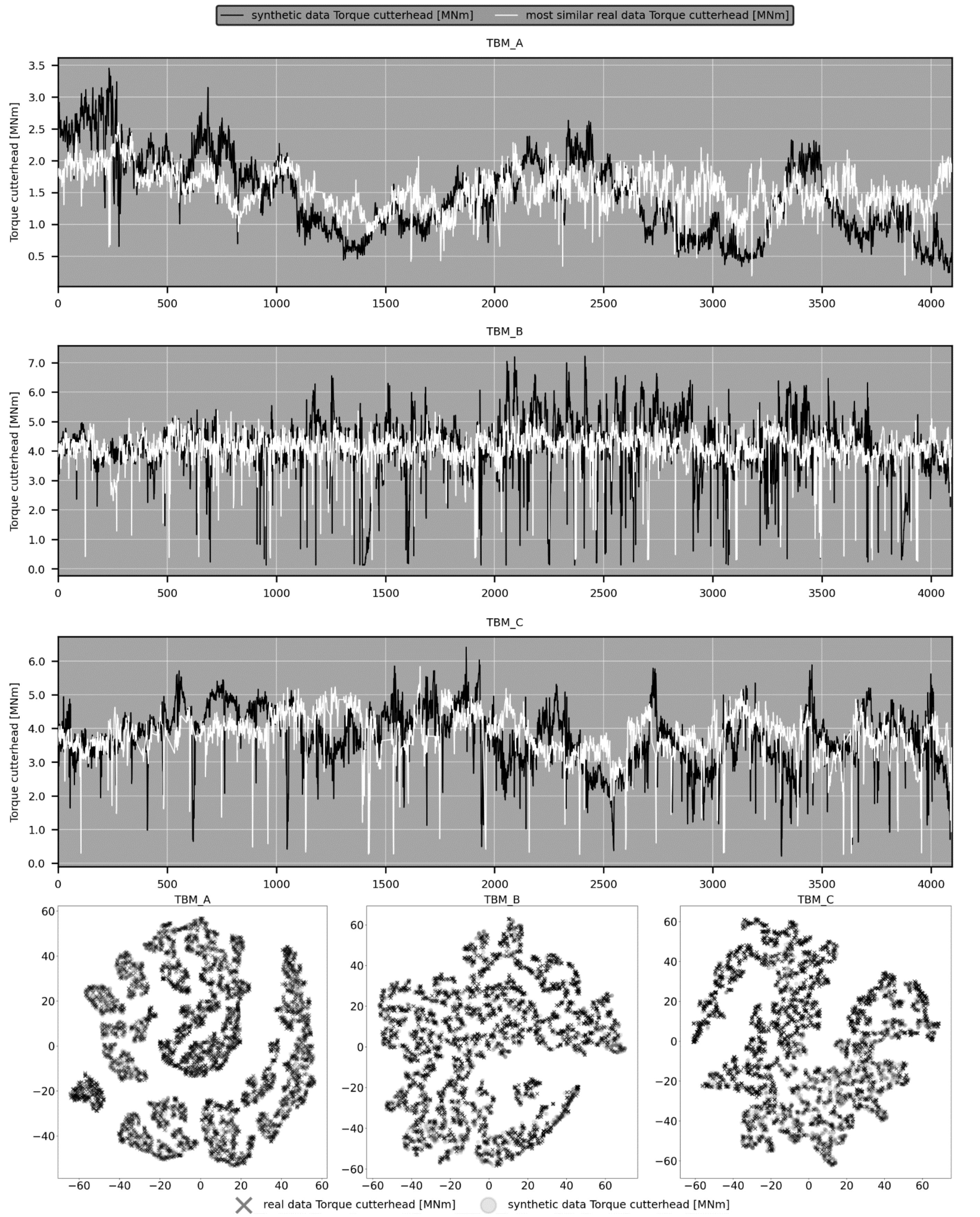

Figure 5: Rows 1-3 show that artificial sequences of the cutterhead torque [MNm] and most similar real TBM training data are sufficiently dissimilar to count as original (x-axis = n datapoints). Row 4: t-SNE dimensionality reduced representation of real and synthetic TBM data shows that both datasets exhibit the same underlying structure and data patterns and thus the synthetic data is representative for the real data.

The generated data which consists of penetration [mm/rot], total advance force [kN] and cutterhead torque [MNm] is then further post-processed to increase the realism of the datasets (see Github repository: src, "DATA_01_postprocessor.py", Python file). The following steps are applied:

- The excavated tunnellength is back calculated by cumulative summation of the generated penetration rate divided by a constant number for cutterhead rotations per minute (TBM A: 6 rpm, TBM B: 5 rpm, TBM C: 5 rpm). The tunnellength is rounded to a precision of centimeters (i.e. meters with two decimals) as is often the case in real TBM operational data. Each of the three generated datasets is limited to 1000 meters in total.
- Stroke numbers are assigned to the datapoints depending on the tunnel length and a constant stroke length of 1.7 meters for all datasets is used.
- After each stroke, a standstill period with a duration between 0.7 to 2 hours is inserted to represent the regripping and support installation process. In the standstill period penetration, total advance force, cutterhead torque and cutterhead rotations are all 0 and the tunnel length and stroke number are kept constant at the last value of the stroke excavation.
- A timestamp with sequentially increasing time is generated that starts at 01.01.2024 (arbitrarily chosen) for all datasets but has different time frequencies for every dataset: (TBM A: 10 s, TBM B: 1 s, TBM C: 10 s).

It needs to be mentioned that the goal of the data synthetization was to create the most realistic TBM operational data in a generic way and not to reproduce any construction site specific data. Values such as the stroke length were therefore taken as the same for all three datasets even though they are not the same in reality. Accordingly, the duration of the standstills was arbitrarily chosen. The realistic, post-processed TBM datasets can be found in the paper's data availability section (see Github repository: data, "TBM_X_1_synthetic_realistic.zip" (replace X with A, B, C for each TBM), zipped .csv files).

3. Processing TBM data for advance classification

The previous section explained how to compute a parameter for TBM advance classification such as the torque ratio (section 2.1) and how realistic and open TBM operational data was created for exemplary purposes of this study (section 2.2). Treating the generated data as real TBM operational data, this section will now elaborate on challenges in the data processing procedure. This procedure is separated into these main steps: i) basic data cleaning/screening, ii) spatial discretization, iii) parameter computation, iv) threshold definition and classification. It must be pointed out that the sequence of these steps may be changed in principle but the order of which the steps are executed can have large impacts on the final result.

If advance conditions are to be classified based on TBM operational data, it is imperative that the processing-procedures, mathematical- or statistical steps and chosen hyperparameters are communicated and agreed upon between all involved parties on site. Even slight deviations from one commonly agreed upon processing pipeline can lead to different advance classifications and thus disputes. For improved transparency and traceability, it is recommended to perform all TBM data processing using programming languages such as Python and to store the code on version tracked code repositories agreed by both parties. The use of spreadsheet calculation software for this purpose is discouraged as the large amount of data makes it not only excessively laborious, but also prone to error and lack of transparency. Code for TBM data processing can be found in the paper's data availability section (see Github repository: src, "DATA_02_analyzer.py", Python file).

3.1. Basic data cleaning

The first step in data processing is to remove standstills/delays/disruptions in excavation process as the advance classification is usually only based on data that is recorded during excavation work of the TBM. Exceptions may exist, as for example presented in Unterlass et al. (2022) where the data from non-advance periods was used to identify rock loads. As proposed by Zhang et al. (2019) and adopted also by Erharter and Marcher (2020), a datapoint is to be seen as a standstill and removed when either one or several of these parameters are equal to 0: cutterhead torque, the advance force, the cutterhead rotations, the penetration. Depending on the TBM's utilization rate, this step typically heavily reduces the overall number of datapoints. In addition, the majority of the TBM manufacturers provide a Boolean/binary flag variable in their data recording indicating “cutterhead rotation” and “TBM advance”. If either of these parameters are flagged as “off”, then the related data can be removed.

TBM operational data is recorded on a regular (temporal) frequency and the recording of the absolute location of the TBM's cutterhead (or other reference points such as the front shield edge) with respect to the tunnel chainage is mostly done with a limited precision of ca. 1 cm. This results in the problem that TBM operational data typically features multiple recorded datapoints for one specific position in the tunnel and the number of datapoints per location is also variable because of different advance speeds. The proposed solution is to take the arithmetic mean of all datapoints with the exact same location and thus create one unique datapoint per location (Erharter and Marcher, 2020; Unterlass et al., 2023). This second step of basic data cleaning again reduces the total number of datapoints significantly, although typically not as much as the first step. Using other methods to spatially merge datapoints such as the median instead of the arithmetic mean can be considered, but experience shows that this has no significant impact on the outcome. (see Github repository: data, "TBM_X_2_synthetic_advance.xlsx" (replace X with A, B, C for each TBM), excel files)

3.2. Spatial discretization

Following initial data cleaning, spatial discretization of the data is required. As, for example, discussed in Erharter and Marcher (2021), an inherent challenge of TBM operational data processing is that the data is equally distributed in time but not in space, but usually the space dimension is the one of interest when it comes to advance classification. The previous step of merging datapoints with the same location in the tunnel lessens the problem to a certain extent but still does so in an unsystematic manner and makes the data analyses vulnerable to the spatial resolution of the TBM data recording. It is thus recommended to systematically discretize the data spatially by i) either spatially interpolating and resampling the data with a defined datapoint spacing along the tunnel length or ii) statistically aggregating (i.e. taking the arithmetic mean or median of) the data in discrete distance steps or intervals along the tunnel. While the former was, for example, shown in Erharter and Marcher (2021), the latter is suggested by the ÖNORM B 2203-2 (Österreichisches

Normungsinstitut, 2023) who recommend to average all datapoints of one stroke of the TBM into one single value through an arithmetic mean. If the stroke-wise averaging approach is chosen, this means that datapoints are averaged for every 1-2 meters. This also has the advantage that the strokes are typically numbered which eases the computation. However, other intervals can be chosen as well and depending on the chosen method of discretization, the total number of datapoints reduces again. After spatial discretization, data smoothing can be considered at this point by applying a moving average window, where the window center is moved along the chainage and the values in the window are taken into account. The recommended window “width” should not exceed 1 m.

3.3. Parameter computation

After cleaning and discretizing the data, the parameter upon which the advance classification is to be based needs to be computed. It is recommended to compute the parameter for the classification after cleaning and discretizing the data to avoid problems related to noise in the data, inhomogeneous data distribution or outliers. Even though we adopt the torque ratio as the exemplary parameter for advance classification in this study as it is the one used in ÖNORM B 2203-2 (Österreichisches Normungsinstitut, 2023), advance classification with other TBM parameters is conceivable and it must be assessed for every construction site which parameter fits best. The specific excavation energy after Teale (1965), for example, correlates well with rock mass behavior in the authors' and others' experience (Bergmeister and Reinhold, 2017). Other parameters such as the specific penetration (Gong and Zhao, 2009), the field penetration index (FPI) (Delisio et al., 2013; Delisio and Zhao, 2014; Hasanpour et al., 2014; Salimi et al., 2019) or the theoretical advance force (Heikal et al., 2021) can be considered as well.

3.4. Threshold definition and advance classification

The last step for TBM operational data based advance classification is to define one or several thresholds that discriminate one advance type from the others. Delisio and Zhao (2014), for example, define thresholds to identify different kinds of blocky rock mass behavior based on a modified version of the FPI, which is the inverse of the Specific Penetration.

In the ÖNORM B 2203-2, two different advance classes are differentiated:

- Regular advance is at hand when the following conditions are met: i) the excavated tunnel geometry fits the cutterhead geometry and there are no or only minor outbreaks; ii) the average torque ratio of a stroke lies within the project specific bounds; iii) the torque ratio is outside of these bounds but this is related to operational and logistical factors; iv) the shield friction is so low that it does not impact the performance (side note: see Erharter et al. (2023a) for more information on TBM shield friction); v) the cutters or other tools for the excavation are not violently damaged and there is no evidence of abnormal cutter wear; vi) only regular support measures and regular mucking is required.
- Exceptional advance is at hand if one or several of the criteria for regular advance are not fulfilled.

As can be seen, the ÖNORM B 2203-2 (2023) is not only relying on the torque ratio as the decisive criteria to discriminate regular from exceptional advance and it is recommended to always consider if further criteria in addition to TBM data parameters are relevant.

Nevertheless, the focus of this work is advance classification based on the TBM data and thus the last step is to define thresholds. This can be done in different ways such as i) defining statistical thresholds that constitute the boundaries of advance classes (e.g. based on standard deviations). While this is a straightforward, understandable and transparent approach, it has limitations in advances that almost exclusively consist of one single class (i.e. almost exclusively regular advance or almost exclusively exceptional advance). ii) Another way of defining thresholds is to conjointly define a reference section of the tunnel where all parties agree that this was regular advance and then define the boundaries accordingly. (ÖNORM B 2203-2, 2023) This reference section of the tunnel should have sufficiently representative length (ideally more than 100 meters) and consist of consecutive and complete strokes only.

Irrespective of way the thresholds were determined, they should be regularly questioned and checked whether they are still fitting for the current excavation conditions and eventually updated. To account for different rock mass types throughout the excavation, different thresholds are possible in one tunnel excavation.

3.5. Exemplary processed TBM operational data

Figure 6 to Figure 8 show exemplary sections of the generated TBM datasets for TBM A, TBM B and TBM C. The data was first synthesized and postprocessed as described in section 2.2 and then processed as if it was real TBM operational data as described in the sections 3.1 to 3.4.

Standstills were removed as described in section 3.1 and datapoints with the same chainage were merged by computing the arithmetic mean of them. Spatial discretization (see section 3.2) was made by computing the arithmetic mean and the median of each single stroke for the parameters penetration, total advance force and cutterhead torque. In real advances, it is not necessary to use different ways of spatial discretization but here it was done to exemplify the effect on the final outcome of this seemingly minor difference (see below). The torque ratio as described in section 2.1 was then computed as the decisive parameter upon which the advance classification should be based. The parameters to compute the torque ratio for the exemplary datasets of this paper are given in Table 1.

Table 1: Input parameters to compute the torque ratio for the exemplary datasets of this paper.

Dataset	**n cutters (n_{disc})**	**Disc cutter radius (R_{DC}) [mm]**	**Cutterhead diameter (D_{CH}) [m]**	**cutterhead torque at idle rotation (M_0) [kNm]**
TBM A	50	241.3	7	180
TBM B	70	241.3	10	400
TBM C	60	241.3	9	220

Lastly, upper and lower thresholds to discriminate regular and exceptional advance were defined as described in section 3.4. The thresholds were set assuming that reference sections of regular advance were defined for the different datasets. The following thresholds were set for each dataset:

- TBM A: lower threshold: 0.35, upper threshold: 0.57

- TBM B: lower threshold: 0.45, upper threshold: 0.57
- TBM C: lower threshold: 0.53, upper threshold: 0.63

Note that all thresholds happen to be below 1 here, but in other excavations, especially upper thresholds > 1 are possible. As given above, two ways of spatial discretization (i.e. arithmetic mean aggregation and median aggregation) were applied to exemplify the impact of different processing methods onto the final classification outcome. Given that and the defined thresholds, different lengths of regular- / exceptional advance were computed for the three different datasets (Table 2).

Table 2: Percentual lengths of advance classification for the three datasets and different spatial discretization methods.

Dataset	**Regular / exceptional advance (arithmetic mean) [%]**	**Regular / exceptional advance (median) [%]**
TBM A	80.3 / 19.7	78.8 / 21.2
TBM B	92.7 / 7.3	94.4 / 5.6
TBM C	83.4 / 16.6	79.6 / 20.4

The fourth rows of Figure 6 to Figure 8 show the torque ratio based advance classification. Strokes where both the arithmetic mean- and the median-based torque ratio are within the specified thresholds or outside of the thresholds are marked in green and red respectively (i.e. green = regular advance, red = exceptional advance). In several strokes, however, either the arithmetic mean- or the median-based torque ratio were inside and outside of the defined boundaries and thus would lead to different classifications of that stroke (marked in orange). (see Github repository: data, "TBM_X_2_synthetic_strokes.xlsx" (replace X with A, B, C for each TBM), excel files)

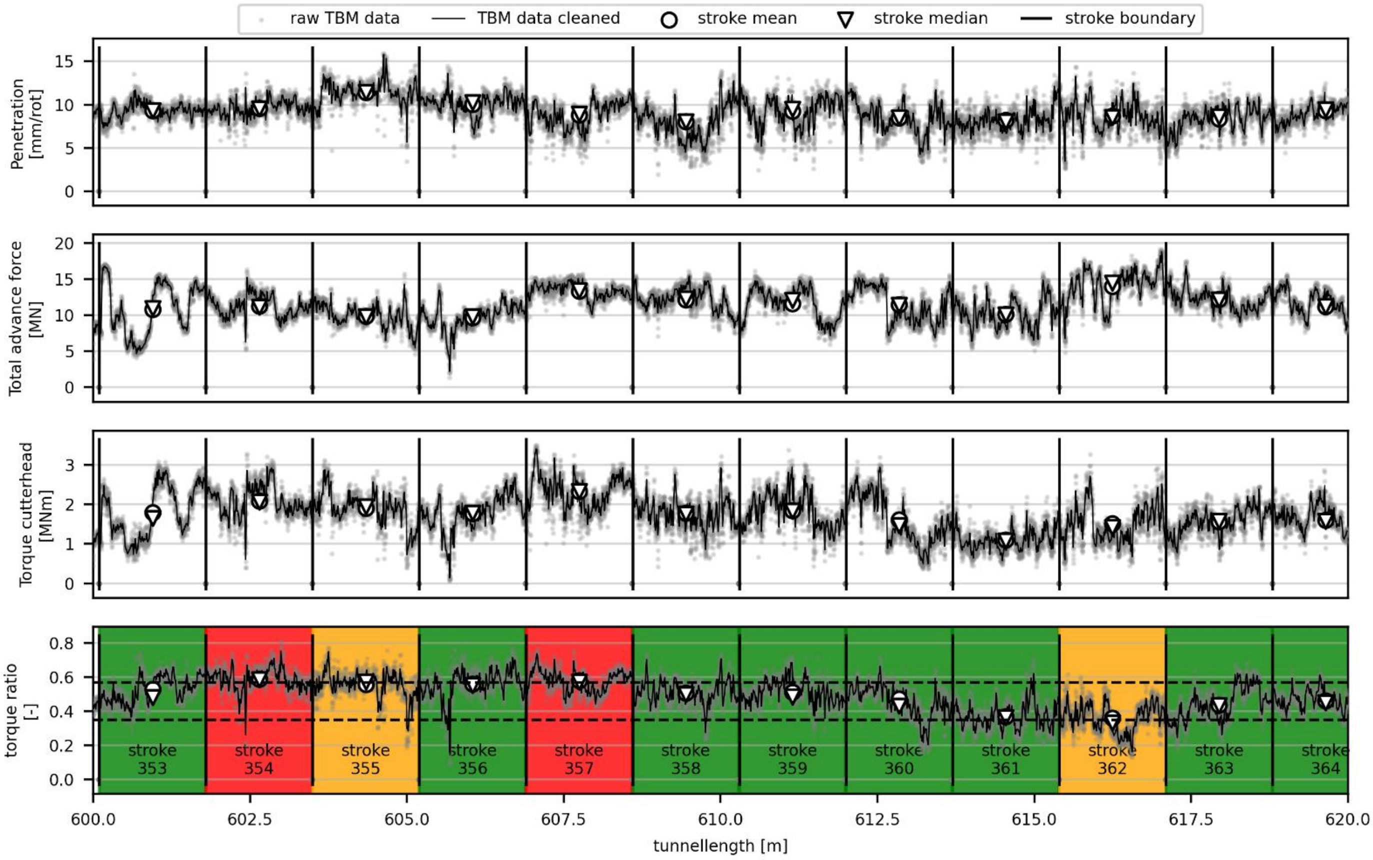

Figure 6: TBM A: 30 meters of synthetic data based on a TBM excavation with an open gripper TBM where the machine was driven based on a constant penetration rate of 10 mm/rot. Explanation for colors in row 4 provided in the text.

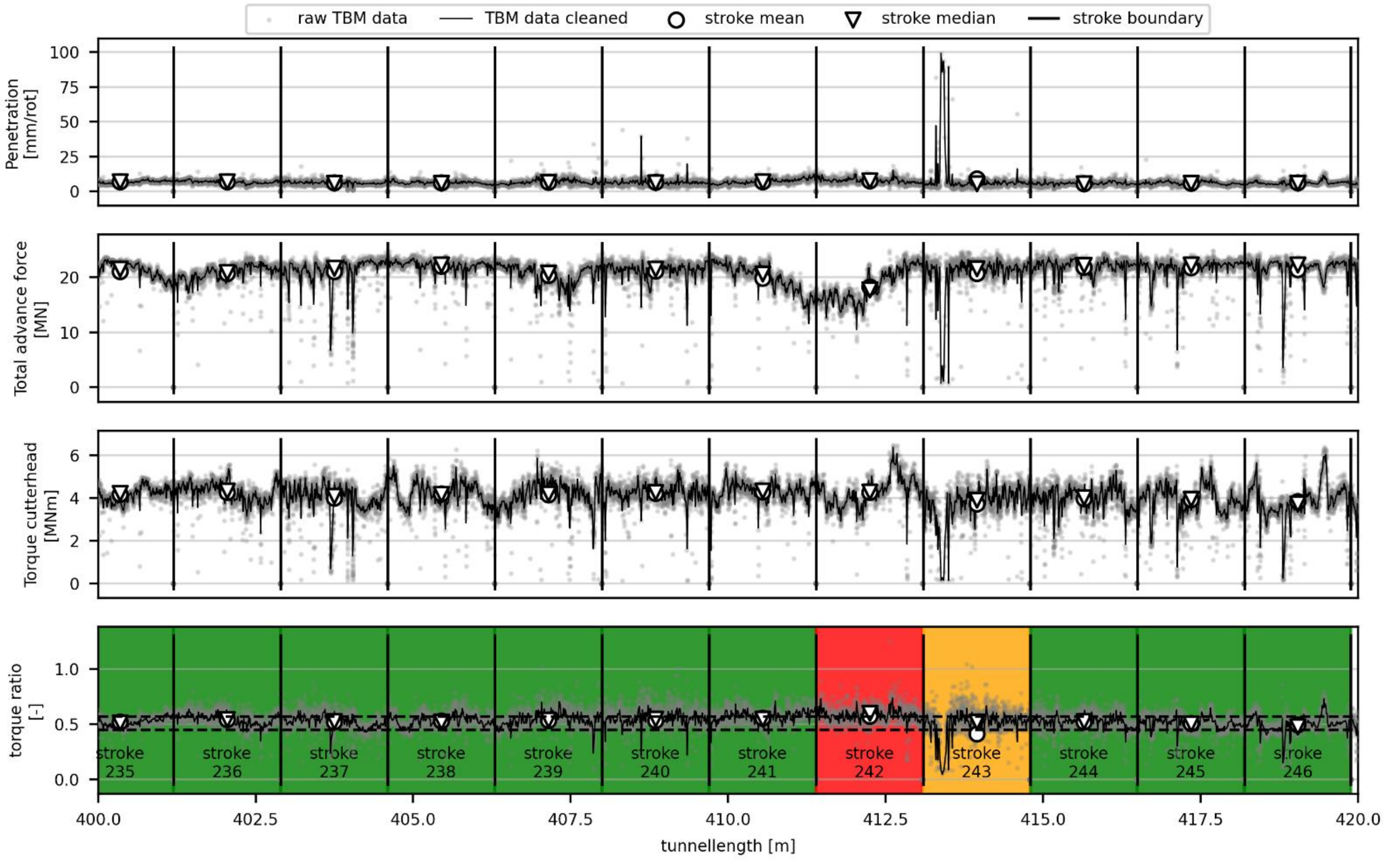

Figure 7: TBM B: 30 meters of synthetic data based on a TBM excavation with a double shield TBM. Explanation for colors in row 4 provided in the text.

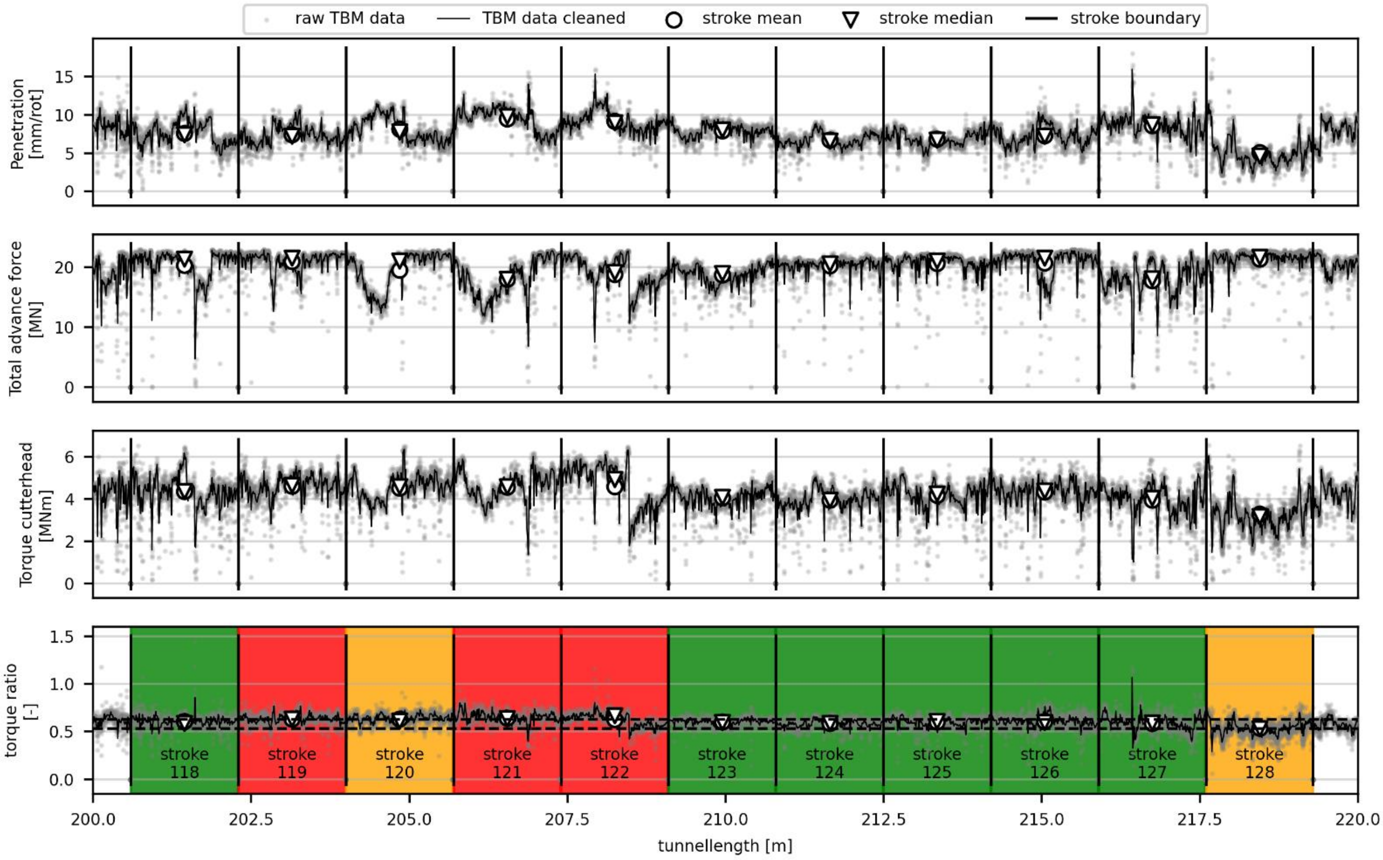

Figure 8: TBM C: 30 meters of synthetic data based on a TBM excavation with an open gripper TBM where the maximum advance force was limited to a bit over 20k MN. Explanation for colors in row 4 provided in the text.

4. Discussion

This paper presents and elaborates on the opportunities and challenges of data-driven TBM advance classification. As TBM operational data is usually subjected to confidentiality requirements, synthetic TBM data was generated by means of generative adversarial networks. While the data is seen as realistic, it is still synthetic and for example lacks some "noisiness" that is typical for real TBM operational data. Nevertheless, the approach serves the purpose of providing the tunnelling community with 3 datasets of 1 km of open TBM operational data that can be used for training and education as well as follow up studies.

In section 3.5, it was shown how an advance classification can be made with the TBM operating parameters to calculate torque ratio for the three datasets. Furthermore, it is shown how only small changes in the processing pipeline of data can affect the final classification. While a difference of 2-4 percent of regular vs. exceptional advance due to different computational approaches might not seem large (Table 2), it can lead to significant cost differences when that affects a tunnel of several kilometres of length. It also needs to be noted that this difference is the result of only one change in the data processing pipeline. Differences will increase if there are more changes or inconsistencies are encountered, which then also complicates the identification of the cause of the difference.

Despite affecting the absolute classification outcome, Figure 6 to Figure 8 also show how processing differences can lead to diverging assessments of individual sections of the tunnel (the orange strokes in this case). While this effect might "average out" over longer tunnel distances, it can lead to disputes and discussions on site if one way of processing classifies a specific stroke as "regular" and another (slightly different) way classifies it as "exceptional". For example, in stroke 355 in Figure 6, the median torque ratio would classify the stroke as exceptional advance while the arithmetic mean torque ratio would classify it as regular. Given that stroke 354 was already exceptional and stroke 357 is also exceptional, this conflicting assessment could lead to a dispute about the total length of this zone of exceptional advance.

The torque ratio has been shown to be well suited for advance classification in several excavations. Nevertheless, it should be noted that the torque ratio's absolute value is of lesser importance than relative changes and patterns within a certain reach that enable recognition of non-regular advance and penetration conditions. Further research into the parameter itself is also encouraged as the presented methodology is strongly simplified. The tangential component of the disc cutter force, for example, (Figure 2) is strongly dependent on the disc cutter geometry, relative orientation of the rock structure and the intact rock properties. Thus, the assumed angle of the disc cutter tangential force should be calibrated in a site-specific, TBM-specific manner once sufficient data and observations are present. Furthermore, perhaps additional operational or composite indices such as FPI or specific energy can be considered for refinement of the operational settings and ground conditions to increase the accuracy and reliability of the Torque ratio for such applications.

5. Conclusion and Outlook

Digitalization is increasingly proving to be a critical driver in mechanized tunneling technology. Data analyses tools have become indispensable, particularly when addressing challenging ground conditions, larger tunnel diameters and lengths, and the growing demand for improved performance and efficiency. During TBM operations, numerous processes run concurrently, each monitored by one or more sensors. With hundreds of sensors, even with data recording interval of least one second, and TBM projects typically spanning several years, the system records and stores billions of data points. The storage and analysis of such big data sets has proven to be challenging, while they present the opportunity of understanding the operations in more detailed levels.

Historically, tunneling data analysis has often been conducted retrospectively and passively and after the fact to evaluate the ground conditions or in the case of claims. However, there is an increasing trend towards real-time data analysis, with a focus on the continuous characterization and classification of TBM system behavior. TBM operating data provides a continuous and uninterrupted record of tunneling conditions, making it an excellent parameter for identifying system behavior. A recently published contractual standard in Austria (ÖNORM B 2203-2) has implemented this concept of “data-driven tunneling classification” into engineering practice. This classification scheme is based on the “torque ratio” and differentiates between “regular” and “exceptional” excavation advances.

In the present paper, the torque ratio is used for illustrative purposes, although other parameters could also be employed for data-driven advanced classification. The paper demonstrates how the torque ratio can be used to pre-classify three different TBM data sets. The torque ratio has been shown to be well-suited for tunneling classification across various excavations. However, it is important to note that the absolute value of the torque ratio is less significant than the relative changes and patterns within the parameter, which allows for the identification of irregular tunneling and penetration conditions. The paper also highlights the challenge of correctly setting thresholds and the sensitivity of the processing methodology, which can significantly influence the final classification.

Data-driven advanced classification offers substantial advantages by ensuring that classifications are both objective and traceable, thereby enhancing the accuracy and reliability of the results. However, if data processing lacks transparency, the objectivity of the classifications may be questioned, potentially leading to concerns about discussions and disputes. Therefore, while data-driven approaches offer numerous benefits, it is crucial to ensure transparency in data processing to maintain the integrity and trustworthiness of the classification process.

This study demonstrates that GANs can effectively synthesize realistic operational data for TBM excavations. The next step involves integrating existing geological and geotechnical data into the model to create a geologically-coupled artificial neural network for process data prediction. Once developed, this network can forecast TBM operational data for new projects and conduct case studies on different TBM types. Further benefits are for example that performance and wear predictions can be based on realistic pre-project data and a multitude of different options can be considered due to the easiness of sample generation once the models are trained. In cases of highly reliable geological forecasts (e.g., constructing a second tunnel after completing the first or completion of remaining tunnel based on the data from the earlier sections of the tunnel), the generated data can facilitate early detection and response to unexpected geotechnical conditions.

With respect to using TBM operational data for advance classification, the following final recommendations are made:

- A detailed step-by-step description for how the TBM data is processed needs to be established for every project and construction site.
- Script- / Code- based processing of the data should be used as it offers superior performance over spreadsheet calculation software in dealing with large amounts of data and it ensures transparent processing.
- The calculation basis needs to be made accessible to all involved parties via a version-controlled repository to facilitate data driven decision making for the operation and financial management of the projects.

Additional work and analysis are underway to refine the process and make it more accessible to parties interested in this approach and make the programs and data analysis process more efficient for practical applications.

Data availability

Exemplary generated TBM data and the code for the generation and analyses of the data can be found in the following Github repository: https://github.com/geograz/TBM_advance_classification

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Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT from OpenAI (https://openai.com/chatgpt/) in order to improve readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Arjovsky, M., Chintala, S., Bottou, L., 2017. Wasserstein Generative Adversarial Networks, in: Proceedings of the 34th International Conference on Machine Learning. PMLR, pp. 214–223.

Asre, S., Anwar, A., 2022. Synthetic Energy Data Generation Using Time Variant Generative Adversarial Network. Electronics 11, 355.

Bach, D., Holzer, W., Leitner, W., Radončić, N., 2018. The use of TBM process data as a normative basis of the contractual advance classification for TBM advances in hard rock. Geomechanik und Tunnelbau 11, 505–518.

Bergmeister, K., Reinhold, C., 2017. Learning and optimization from the exploratory tunnel - Brenner Base Tunnel. Geomechanik und Tunnelbau 10, 467–476.

Delisio, A., Zhao, J., 2014. A new model for TBM performance prediction in blocky rock conditions. Tunnelling and Underground Space Technology 43, 440–452.

Delisio, A., Zhao, J., Einstein, H.H., 2013. Analysis and prediction of TBM performance in blocky rock conditions at the Lötschberg Base Tunnel. Tunnelling and Underground Space Technology 33, 131–142.

Erharter, G.H., Goliasch, R., Marcher, T., 2023a. On the Effect of Shield Friction in Hard Rock TBM Excavation. Rock Mech Rock Eng. https://doi.org/10.1007/s00603-022-03211-0.

Erharter, G.H., Hansen, T.F., Qi, S., Bar, N., Marcher, T., 2023b. A 2023 perspective on Rock Mass Classification Systems, in: Proceedings of the 15th ISRM Congress 2023 & 72nd Geomechanics Colloquium. CHALLENGES IN ROCK MECHANICS AND ROCK ENGINEERING. 15th ISRM Congress 2023 & 72nd Geomechanics Colloquium, Salzburg / Austria. 9.-14. October 203, pp. 758–763.

Erharter, G.H., Marcher, T., 2020. MSAC: Towards data driven system behavior classification for TBM tunneling. Tunnelling and Underground Space Technology 103, 103466.

Erharter, G.H., Marcher, T., 2021. On the pointlessness of machine learning based time delayed prediction of TBM operational data. Automation in Construction 121, 103443.

Farrokh, E., Rostami, J., 2008. Correlation of tunnel convergence with TBM operational parameters and chip size in the Ghomroud tunnel, Iran. Tunnelling and Underground Space Technology 23, 700–710.

Farrokh, E., Rostami, J., 2009. Effect of adverse geological condition on TBM operation in Ghomroud tunnel conveyance project. Tunnelling and Underground Space Technology 24, 436–446.

Gong, Q.M., Zhao, J., 2009. Development of a rock mass characteristics model for TBM penetration rate prediction. International Journal of Rock Mechanics and Mining Sciences 46, 8–18.

Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A., Bengio, Y., 2014. Generative Adversarial Networks. In: Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, K. Q. Weinberger (Eds.) Advances in Neural Information Processing Systems 27. Curran Associates, Inc, pp. 2672–2680.

Hasanpour, R., Rostami, J., Barla, G., 2015. Impact of Advance Rate on Entrapment Risk of a Double-Shielded TBM in Squeezing Ground. Rock Mech Rock Eng 48, 1115–1130.

Hasanpour, R., Rostami, J., Schmitt, J., Ozcelik, Y., Sohrabian, B., 2020. Prediction of TBM jamming risk in squeezing grounds using Bayesian and artificial neural networks. Journal of Rock Mechanics and Geotechnical Engineering 12, 21–31.

Hasanpour, R., Rostami, J., Ünver, B., 2014. 3D finite difference model for simulation of double shield TBM tunneling in squeezing grounds. Tunnelling and Underground Space Technology 40, 109–126.

Heikal, G., Erharter, G.H., Marcher, T., 2021. A new parameter for TBM data analysis based on the experience of the Brenner Base Tunnel excavation. IOP Conf. Ser.: Earth Environ. Sci. 833, 12158.

Holzer, W., Wagner, O.K., Leitner, W., 2021. Überarbeitung der österreichischen Werkvertragsnorm ÖNorm B 2203-2 für den kontinuierlichen Vortrieb. Geomechanics and Tunnelling 14, 730–739.

Liu, Q., Wang, X., Huang, X., Yin, X., 2020. Prediction model of rock mass class using classification and regression tree integrated AdaBoost algorithm based on TBM driving data. Tunnelling and Underground Space Technology 106, 103595.

Liu, Z., Li, L., Fang, X., Qi, W., Shen, J., Zhou, H., Zhang, Y., 2021. Hard-rock tunnel lithology prediction with TBM construction big data using a global-attention-mechanism-based LSTM network. Automation in Construction 125, 103647.

Maidl, B., Schmid, L., Ritz, W., Herrenknecht, M., 2008. Hardrock tunnel boring machines. Ernst, Berlin, 343 pp.

Ng, A., Jordan, M., 2001. On Discriminative vs. Generative Classifiers: A comparison of logistic regression and naive Bayes, in: Advances in Neural Information Processing Systems. MIT Press.

ÖGG, 2023. Richtlinie Geotechnische Planung von Untertagebauten Zyklischer und kontinuierlicher Vortrieb: Gebirgscharakterisierung und Vorgangsweise zur nachvollziehbaren Festlegung von bautechnischen Maßnahmen während der Planung und Bauausführung, 83 pp.

Österreichisches Normungsinstitut, 2023. Untertagebauarbeiten ÖNORM B 2203-2:2023 03 01: Teil 2: Kontinuierlicher Vortrieb 91.010.20; 93.020, 60 pp.

Park, N., Mohammadi, M., Gorde, K., Jajodia, S., Park, H., Kim, Y., 2018. Data synthesis based on generative adversarial networks. Proc. VLDB Endow. 11, 1071–1083.

Pearson, K., 1901. LIII. On lines and planes of closest fit to systems of points in space. The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science 2, 559–572.

Radoncic, N., Hein, M., Moritz, B., 2014. Determination of the system behaviour based on data analysis of a hard rock shield TBM / Analyse der Maschinenparameter zur Erfassung des Systemverhaltens beim Hartgesteins-Schildvortrieb. Geomechanik und Tunnelbau 7, 565–576.

Radončić, N., Purrer, W., Pichler, K., 2019. A model for fair compensation of construction costs in TBM tunneling: A novel contribution. In: Peila, D., Viggiani, G., Celestino, T. (Eds.) Tunnels and Underground Cities: Engineering and Innovation meet Archaeology, Architecture and Art. CRC Press, pp. 4567–4573.

Rostami, J., 1997. Development of a force estimation model for rock fragmentation with disc cutters through theoretical modeling and physical measurement of crushed zone pressure. Dissertation, Colorado, 271 pp.

Rostami, J., 2013. Study of pressure distribution within the crushed zone in the contact area between rock and disc cutters. International Journal of Rock Mechanics and Mining Sciences 57, 172–186.

Rostami, J., Ozdemir, L., 1993. A New Model for Performance Prediction of Hard Rock TBMs. In: Bowerman, L.D. (Ed.) Proceedings / 1993 Rapid Excavation and Tunneling Conference, [1993 RETC], Boston, Massachusetts, June 13-17, 1993. Society for Mining Metallurgy and Exploration (SME) of the American Institute of Mining Metallurgical and Petroleum Engineers, Littleton, Colo, pp. 793–809.

Salimi, A., Rostami, J., Moormann, C., 2019. Application of rock mass classification systems for performance estimation of rock TBMs using regression tree and artificial intelligence algorithms. Tunnelling and Underground Space Technology 92, 103046.

Teale, R., 1965. The concept of specific energy in rock drilling. International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts 2, 245.

Thuro, K., 2002. Geologisch-felsmechanische Grundlagen der Gebirgslösung im Tunnelbau: Habilitationsschrift. In: Münchner Geologische Hefte. Reihe B, pp. 1–160.

Unterlass, P.J., Erharter, G.H., Marcher, T., 2022. Identifying Rock Loads on TBM Shields During Standstills (Non-Advance-Periods). Geotech Geol Eng. https://doi.org/10.1007/s10706-022-02263-x.

Unterlass, P.J., Erharter, G.H., Sapronova, A., Marcher, T., 2023. A WGAN Approach to Synthetic TBM Data Generation. In: Gomes Correia, A., Azenha, M., Cruz, P.J.S., Novais, P., Pereira, P. (Eds.) Trends on Construction in the Digital Era, vol. 306. Springer International Publishing, Cham, pp. 3–19.

van der Maaten, L., Hinton, G., 2008. Visualizing Data using t-SNE. Journal of Machine Learning Research 9, 2579–2605.

Xue, Y.-D., Luo, W., Chen, L., Dong, H.-X., Shu, L.-S., Zhao, L., 2023. An intelligent method for TBM surrounding rock classification based on time series segmentation of rock-machine interaction data. Tunnelling and Underground Space Technology 140, 105317.

Zhang, Q., Liu, Z., Tan, J., 2019. Prediction of geological conditions for a tunnel boring machine using big operational data. Automation in Construction 100, 73–83.