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Predictive machine learning in earth pressure balanced tunnelling for main drive torque estimation of tunnel boring machines

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ABSTRACT

Designing the main drive motor capacity of Earth Pressure Balanced Tunnel Boring Machines (EPB TBMs) is a crucial task for every EPB tunnelling project. The machine needs to be equipped with sufficient power to master the geotechnical conditions of the respective project. On the other hand, overpowering the machine should be avoided for economic and sustainability reasons. Main drive torque estimation for EPB TBMs is challenging due to a multitude of impact factors and reciprocal mechanisms between the geotechnical conditions and the tunnelling process. In EPB TBM tunnelling active tunnel face support is achieved in soft and mixed ground or weak and unstable rock by generating a pressurized earth paste in the tool gap and excavation chamber of the machine. Complexity arises due to tribological and rheological effects of the active tunnel face support. These elements of uncertainty, the expected main drive torque is frequently overestimated to prevent a jamming of the machine in the ground. Mean main drive torque values often lie below 50 % of the installed nominal main drive torque capacity. In scope of this research machine learning algorithms, such as regressions, decision trees, tree ensembles, support vector machines and gaussian process regressions, have been used to predict the main drive torque. Models have been trained and tested on data collected from 9 different reference projects and validated on the data of 3 additional reference projects to test the transferability of the model. TBM diameters of the reference projects vary between 6,5 and 15,9 m and TBMs have been operating in a wide range of geotechnical boundary conditions. Different feature selection algorithms have been used and prediction results have been compared to models trained on manually selected features. Models using tree ensembles and manually selected features showed best prediction results and model performance. The machine learning approach returned a smaller and more accurate torque estimation range than traditional estimation approaches and prediction accuracy has been improved. Transparent and robust tree ensembles proofed to be suitable tools for TBM torque estimation.

1. Introduction

At present EPB TBMs are the predominant TBM type used in unstable mixed ground conditions, where an active face support is required to stabilize the ground. The tunnel face is supported by the excavated soil or rock material, which is transformed into an earth paste and pressurized to counterbalance earth and water pressures. The machine is pressed forward into the ground and the extraction of the earth paste from the excavation chamber is controlled at the same time. Turning the cutting wheel during ground excavation and TBM advance causes friction between the steel structure of the cutting wheel, the ground, and the earth paste. The turning cutting wheel needs to overcome the inner shear strength of the earth paste at the openings of the cutting wheel and the torque to remove the undisturbed ground with the excavation tools. Hence, the TBM layout must consider sufficient main drive motor capacity including an appropriate safety margin to handle these loads. Several factors are influencing these loads. TBM design related impact factors are e.g., TBM diameter, opening ratio of the cutting wheel, type, number, and position of cutting tools. Geotechnical impact factors comprise ground strength, mineralogy, grain sizes, content of fines, Atterberg limits, ground structure and texture, overburden, and ground water. Tribological factors are influencing the main drive torque due to

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friction between ground or earth paste and cutting wheel, lubrication by foam, water or additives, adhesion, wear, and thermal energy loss. Further reciprocal effects between TBM operation and ground are related to the rheology of the earth paste, the impact of the TBM operation mode and advance rate of the machine.

First estimation models for the main drive of tunnel boring machines have been published in the 1970s for tunnel projects in hard rock. Mellor & Hawkes (Mellor and Hawkes, 1972) and Roxborough & Phillips (Roxborough and Phillips, 1975) were among the first to examine the main drive torque and related forces acting between rock, cutting tools and cutterhead. Further approaches have been published e.g. by (Snowdon et al., 1982; Sanio, 1985; Barton, 2000; Gong and Zhao, 2009). Two most common approaches today for torque estimation in hard rock were published by (Ozdemir, 1977) and (Bruland, 2000) calculating torque components using empirically determined coefficients. In stable sections of the tunnel alignment, EPB TBMs can be operated in open mode without providing active face support. For these sections, the approaches for hard rock TBMs can be applied also for EPB TBMs. For EPB tunnelling in soft and mixed ground these approaches are not suitable since they do not account for soft ground conditions, such as friction forces between earth paste and steel structure of the cutting wheel, inner shear forces of the earth paste at the openings of the cutting wheel or the influence of soil conditioning, clogging of the ground, etc.

Consequently, a new approach was required to estimate the main drive torque for this type of TBM and an empirical approach has been published by (Krause, 1987) based on experiences with small size TBMs up to 8 m diameter.

$$M_T = \alpha^* D^3 \tag{1}$$

where the main drive torque MT is calculated in kNm using the TBM diameter D in m and an empirical factor α to account for all impact factors influencing the main drive torque (1). The recommendations for selection of the empirical factor have been adapted later by (JSCE, Japan Society of Civil Engineers, 2007) based on extended experience with larger EPB TBMs and a wider range of project boundary conditions using values ranging between 10 and 25 kN/m^2.

With increasing tunnel dimensions and continuously increasing TBM diameters this approach showed some limitations, because the torque estimation range widened. Numerous theoretical approaches have been published, where torque components are calculated to improve the load prediction, e.g. by (Wittke, 2007; Song et al., 2010; Wang et al., 2012; Zhang et al., 2014; González et al., 2016; Avunduk and Copur, 2018) or (Zhou and Zhai, 2018). One of the most cited approaches has been published by (Shi et al., 2011), who identified eight torque components (2):

$$M_T = T_1 + T_2 + T_3 + T_4 5 + T_5 + T_6 + T_7 + T_8 \tag{2}$$

with T1 the friction between the front of the cutting wheel and the muck, T2 the friction between the circumference of the cutting wheel and the muck, T3 the friction between the back of the cutting wheel and the muck, T4 the ground cutting and excavating process component, T5 the shearing of muck at cutting wheel openings, T6 the friction between mixing bars and muck, T7 the friction generated by the bearing system and finally T8 to account for sealing losses. Theoretical approaches differ by project boundaries and impact factors. Most theoretical approaches use the friction coefficient μ to describe the friction between the earth paste and the cutting wheel. Recommendations for the friction coefficient μ range from 0,25 (Gehring, 2009) to 0,73 (Song et al., 2010).

Both parameters, α and μ, have a substantial impact on the main drive torque prediction while showing uncertainties and limitations (Godinez et al., 2015) and (Ates et al., 2014). The existing state-of-the-art prediction models are based on input parameters, which are often difficult to determine during the design phase of a project and prone to uncertainty.

A machine learning (ML) approach has been selected to reduce uncertainties and improve prediction accuracy based on the experience gained on comparable projects by using the data to train, test and validate ML models. Data analysis and machine learning applications in TBM tunnelling are not new and several approaches have been published in recent years, mainly to predict TBM performance using a range of algorithms. (Acaroglu, 2011) used a fuzzy logic approach for hard rock TBMs, (Maji and Theja, 2017) used a regression model for TBM performance prediction. (Salimi et al., 2015; Salimi et al., 2018) used various algorithms for projects in hard rock and mixed ground conditions, whereas (Armaghani et al., 2018) selected a gene expression programming model for hard rock and mixed ground conditions. (Mokhtari and Mooney, 2019) used a Monte Carlo approach to account for uncertainties, (Gao et al., 2019) and (Cachim and Bezuijen, 2019) generated neural networks to predict TBM operating parameters, (Hong et al., 2021) used regression analysis and long short- term memory (LSTM) networks and (Ucar et al., 2022) used statistical modelling to predict the cutterhead torque for EPB TBMs.

All these authors based their research on data of one project at a time to predict target values for the same project or projects from the same area. These predictive models are suitable to optimize TBM operation during an EPB project, but they show limited transferability to new projects with different boundary conditions. Especially for large scale EPB projects a precise load estimation is crucial for a proper TBM layout. Therefore, the aim of this study is to provide a transferable machine learning approach suitable to be applied on new projects during the design phase of a TBM, which returns a more precise range of the main drive torque to optimize the TBM layout.

2. Methodology

2.1. Reference projects

In scope of this study, data from 12 different reference projects has been collected, whereas 9 projects were used for training and testing the ML models, and 3 projects were used for model validation. The following table (Table 1) gives an overview over the reference projects, including TBM diameter, main type of geology as well as installed nominal torque and monitored mean torque per ring.

Torque values are measured using sensors installed on the TBM and monitored via the programmable logic controller (PLC) of the machine.

Table 1
Reference projects with validation projects marked in grey.

project	diameter [m]	geology	nominal torque, installed [MNm]	mean torque / ring, monitored [MNm]	max torque / ring, monitored [MNm]
A	6,5	clay, sand	4,5	2,47	3,79
B	7,1	limestone	4,8	2,36	7,44
C	7,1	clay	9,3	3,46	3,72
D	8,1	clay	7,0	4,32	5,01
E	9,8	marl, limestone	17,9	6,23	14,06
F	11,1	marl, sandstone	19,4	9,60	15,03
G	12,1	siltstone, clay, gravel	38,0	7,13	16,68
H	12,6	sandstone, clay	16,5	12,68	17,31
I	14,4	sandstone	68,2	19,00	39,29
J	15,2	claystone, gypsum	95,9	23,41	48,35
K	15,5	claystone, sandstone, marl, breccia	94,8	32,82	65,7
L	15,9	marl, limestone, sandstone	72,4	25,59	41,5

Maximum torque values are the maximum registered values per segment ring. In scope of this analysis, only TBM data during advance mode of the machine is considered. Null values during ring building and down times of the machine are not included in the calculation of mean values.

2.2. Machine learning approach

To improve the prediction accuracy of the main drive torque and prevent future overpowering of EPB TBMs a supervised machine learning model has been set up, based on the following iterative workflow (Fig. 1):

Data collection and set up of the data base included selection of the reference projects. Main goal was to select projects in the diameter range between 6 and 16 m, which is representative for most metro, rail and road tunnelling projects. The reference projects should cover various geotechnical and project related boundary conditions. Finally, the projects were selected after evaluation of quality and quantity of monitored and collected data and project information. Data preparation and engineering comprised cleaning, noise reduction, outlier evaluation, standardization and normalization, dimensionality reduction (principal component analysis PCA) and modification of frequency distribution (log transformation). Unsupervised methods such as pattern recognition and clustering (hierarchical clustering, k-means clustering, neural networks) have been applied. Feature selection algorithms (FSA) such as Pearson's and Spearman's coefficient with limited threshold of coefficients and neighborhood component analysis NCA using gradient ascent (Goldberg et al., 2005) and a regularization parameter λ as input variable (Yang and Laaksonen, 2007; Yang et al., 2012) have been applied. The RreliefF algorithm, established by (Kira and Rendell, 1992) and further developed by (Robnik Sikoja and Kononenko, 2003), has been applied. Prediction results of these data sets have been compared to prediction results of manually selected features. The following 13 impact factors were manually selected as input features, comprising project and TBM operation related data as well as geotechnical data:

- TBM diameter [m]
- cutting wheel opening ratio [%]
- cohesion [kN/m^2]
- inner friction angle [°]
- unconfined compressive strength [MN/m^2]
- plasticity index [%]
- consistency index [-]
- rotation speed [rpm]
- penetration [mm/rot]
- thrust force [MN]
- mean earth pressure [bar]
- apparent muck density crown [kN/m^3]
- apparent muck density invert [kN/m^3]

In total, 19 algorithms have been used to generate torque prediction models (see Table 4), ranging from regression models, CART algorithms, tree ensembles, support vector machines to Gaussian process regressions (Inc, 2020). The models have been trained and tested using cross validation. The results of the model predictions have been evaluated not only based on the prediction accuracy. The following aspects have been considered:

- accuracy, metrics: coefficient of determination R^2, root mean square error RSME; for FSA additionally: MSE mean squared error and mean absolute error MAE
- transferability, metrics: total error of model validation (comparing prediction versus monitored values on 3 validation projects)
- prediction reliability: residual evaluation, evaluating trends of prediction error
- interpretability, transparency of learning process
- robustness, impact of noise, missing values, outliers
- availability and reliability of crucial input features (problem with selection of a-value or friction coefficient m)

For the manually selected data set a sensitivity analysis has been performed. Variation of the features using minimum and maximum values and comparing prediction results showed the impact of these features. Finally, the models have been validated by making predictions for 3 reference projects using the monitored and collected project data as input features and compare the result with monitored torque values. The data of these 3 validation projects has not been used for training and testing of the models.

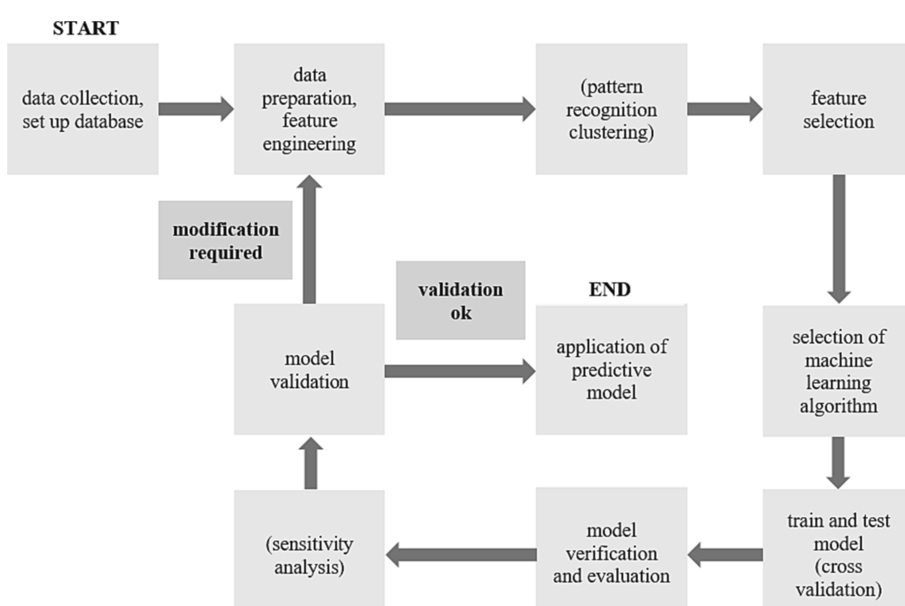

Fig. 1. Iterative workflow of machine learning approach.

3. Results & discussion

3.1. State-of-the-art approaches vs monitored main drive torque

In general, the nominal torque capacity installed on EPB TBMs is designed for normal operation. Exceptional and breakout torque capacity of the main drive is installed to handle maximum torque spikes, occurring e.g., after down times when restarting the machine. The following table (Table 2) shows back calculated empirical α values based on Equation (1). Utilization is calculated comparing nominal torque capacity with mean values of the monitored main drive torque.

The following graph (Fig. 2) shows prediction results using the empirical approach marked with triangular shapes and the theoretical approach marked with diamond shapes compared to the monitored values marked with circular shapes in six different homogenous sections of reference project I. Furthermore, the influence of the recommended α- and μ-range is visualized in the width of the respective main drive torque predictions for each section, which shows the difference between the prediction using an α of 10 and α of 25 and a μ of 0,1 and a μ of 0,7.

The graph in Fig. 2 shows that the range of empirical and theoretical approaches exceeds the monitored torque values by far, depending on the selected α- and μ-values. Hence, for the design of EPB TBMs, the application of those approaches is limited since the prediction models are sensitive and responsive to the selected α- and μ-values and return a wide range of possible torque requirements.

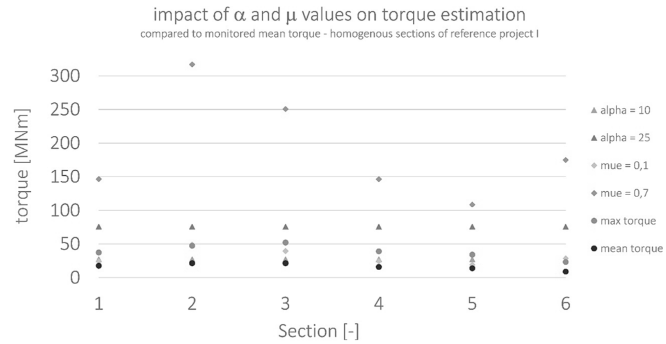

Fig. 2. Comparison of empirical and theoretical approach versus monitored torque.

3.2. Feature selection and sensitivity analysis

Ground strength is a decisive impact factor for the main drive torque. No FSA method selected any geotechnical impact features except NCA, selecting inner friction angle, plastic limit and undrained shear strength. Operational parameters such as thrust force and rotation speed of the cutting wheel are influencing the torque. Rotation speed was only identified as influential by Spearmans correlation. RreliefF selected ony 5 TBM operational parameters, no geotechnical features, virtual sensors or TBM design features. TBM diameter was only identified as important impact factor by Peasons and Spearmans correlation.

Table 3 shows the results of the FSA methods, comparing the prediction accuracy of the best performing ML algorithms using the data set selected by the respective FSA method. It is demonstrated that the manually selected data set returns best results.

Table 2
Back calculated a values and utilization of reference projects.

project	diameter [m]	geology	back calculated α			utilization [%]
			α installed	α mean	α max	
A	6,5	clay, sand	16,3	9,0	13,8	55 %
B	7,1	limestone	19,6	12,1	20,8	62 %
C	7,1	clay	13,3	6,6	10,4	49 %
D	8,1	clay	17,4	6,5	9,4	37 %
E	9,8	marl, limestone	19,1	6,6	14,9	35 %
F	11,1	marl, sandstone	14,1	7,0	11,0	50 %
G	12,1	siltstone, clay, gravel	21,5	4,8	9,4	22 %
H	12,6	sandstone, clay	8,3	6,3	8,7	77 %
I	14,4	sandstone	22,8	6,4	13,2	28 %
J	15,2	claystone, gypsum	27,3	6,7	13,8	24 %
K	15,5	claystone, sandstone, marl, breccia	25,5	8,8	17,6	35 %
L	15,9	marl, limestone, sandstone	18,0	6,4	10,3	35 %

Table 3
Results fsa – comparison of model performance.

FSA	best performing ML algorithm	R^2	RMSE	MSE	MAE
Pearson's Coefficient of Correlation	Gaussian Process, Exponential	0,93	0,28	0,08	0,15
Spearman's Coefficient of Correlation	Gaussian Process, Rational Quadratic	0,94	0,27	0,07	0,16
RreliefF	Gaussian Process, Rational Quadratic	0,93	0,22	0,05	0,11
NCA	Gaussian Process, Rational Quadratic	0,95	0,23	0,05	0,13
Manual Selection	Gaussian Process, Exponential	0,96	0,19	0,04	0,11

3.3. Machine learning approach

Prediction results are summarized in Table 4, showing R^2 and RMSE values to assess model accuracy as well as prediction results and total prediction error for all three validation projects. With R^2 values > 0,83 and RMSE in the range of 2–4 MNm, accuracy metrics returned very good results for all algorithms with manually selected input features. Transferability of the prediction model was demonstrated using the data of the three validation projects with TBM diameters from 6,5 m to 15,9 m in soft- and mixed ground conditions. Total validation errors vary in a wide range between 2 and 63 MNm, depending on the algorithm used. However, both tree ensembles, bagged and boosted, show very good results regarding R^2 and RMSE as well as total validation error. The bagged tree ensemble shows best results with R^2 of 0,96, RSME of 1,9277 MNm and a total validation error of 2,39 MNm, all three values closest to the respective optimum value. Especially the large diameter validation project has been estimated with very good accuracy, where the state-of-the-art approaches fail. Furthermore, tree ensembles are transparent regarding the decision-making process, and robust regarding noise, missing values, or outliers.

Both parameters, advance speed, and conditioning (injected liquids to the front, FIR, FER) have been included in the database. The database consists of 64 features (TBM data, geotechnical data, project data and virtual sensors) and 16,209 samples (mean values per segment ring). Prediction results of machine learning models with different sets of input features including advance speed and conditioning have been compared, showing best results for the model with the 13 selected input features referred to in this paper. For machine learning approaches statistical methods are potentially biased. Machine learning models are commonly evaluated using resampling methods rather than statistical methods. In this case, a 5-fold cross-validation has been used to avoid overfitting of the models.

Table 4
Results of machine learning models using manually selected input features.

ML algorithms	R^2	RMSE [MNm]	prediction [MNm]			
			project L	project G	project A	total error
optimum value	**1**	**0**	**25,93**	**6,86**	**2,49**	**0**
Linear Regression	0,86	3,9018	28,02	16,06	1,64	12,15
Linear Regression, Interactions	0,93	2,722	39,97	9,09	0,48	18,28
Linear Regression, Robust	0,83	4,1891	30,80	19,75	2,91	18,17
Linear Regression, Stepwise	0,93	2,7267	40,79	8,99	0,45	19,03
Fine Decision Tree	0,95	2,2846	26,30	8,91	2,64	2,55
Medium Decision Tree	0,95	2,2285	26,51	8,73	2,82	2,77
Coarse Decision Tree	0,95	2,3547	25,03	8,88	2,97	3,39
Support Vector Machine, Linear	0,85	3,9803	29,91	17,29	2,61	14,52
Support Vector Machine, Quadratic	0,93	2,6829	39,63	9,88	−3,56	22,77
Support Vector Machine, Cubic	0,94	2,469	9,12	17,09	38,12	62,67
Support Vector Machine, Fine Gaussian	0,94	2,5432	16,23	13,38	10,65	24,39
Support Vector Machine, Medium Gaussian	0,95	2,3008	19,16	10,02	5,90	13,34
Support Vector Machine, Coarse Gaussian	0,89	3,3921	29,13	12,10	4,19	10,13
Boosted Tree Ensemble	0,94	2,4475	23,97	8,16	2,74	3,51
Bagged Tree Ensemble	**0,96**	**1,9277**	26,10	8,77	2,81	**2,39**
Gaussian Process, Squared Exponential	0,96	2,0439	18,92	8,66	5,81	12,13
Gaussian Process, Matern 5/2	0,96	1,9988	19,34	10,54	6,14	13,91
Gaussian Process, Exponential	0,96	1,9818	24,83	11,75	3,29	6,79
Gaussian Process, Rational Quadratic	0,96	2,1171	23,56	12,29	4,56	9,88

The presented machine learning model considers the advance speed [mm/min] by using penetration [mm/rot] and rotation speed of the cutting wheel [rpm]. In machine learning the use of correlated features can lead to biased results. Using the advance speed as additional input factor would cause such bias by overestimating the impact of these three parameters. Ground conditioning has been considered by using the sum of injected liquids to the front for an additional machine learning model (not included in this paper). The following 14 input features have been selected for this additional model: diameter, degree of cutting wheel opening, cohesion, inner friction angle, UCS, plasticity index, consistency index, rotation speed, penetration, thrust force, mean earth pressure, sum of injected liquids, apparent muck density crown and apparent muck density invert. However, the prediction accuracy decreased when comparing the model with the results of the model without sum of injected liquids (Table 5).Table 6

It has been assumed that the total amount of injected liquid adds a certain amount of uncertainty to the prediction. Hence, the models have been trained, tested, and validated using 13 features, neglecting the injected liquids, and using only the apparent muck density in the invert and crown as indicator for the muck consistency. Further research is required to study the impact of the conditioning on the torque in more detail e.g., by improving the monitoring of the conditioning system and using the data for further machine learning projects. This question has not been in the focus of the present research.

So far, the study investigated normal TBM operation and compared mean torque values with the nominal installed torque. The more critical part regarding jamming of a machine are the maximum torque values. Table 1 shows mean and maximum torque values recorded throughout the respective projects and only in two cases, the maximum recorded torque exceeds the nominal installed torque, for project B and H. In those cases, the exceptional or breakout torque reserve can be used to prevent jamming of the machine, but only for a limited period of time. To estimate the maximum torque values to be expected for e.g., startup operation after down times, throughout a project, all monitored mean and maximum values per ring have been compared, showing very good correlation. Hence, maximum torque values for startup operation have been estimated based on the 95 % confidence interval of the correlation between mean and maximum torque values per ring of all reference projects:

$$ML_{max,\ 95\%\ confidence} = 6 + 1,35 * ML_{mean}$$

For small diameter projects with mean main drive torque < 5 MNm the estimation based on the linear fit of the correlation between mean and maximum torque values per ring of all reference projects returns more accurate results:

$$ML_{max,\ linear\ fit} = 1,35 * ML_{mean}$$

Purpose of this research was to improve torque prediction for the nominal torque capacity during normal operation. The torque reserve has been accounted for by analyzing maximum torque values, which are mainly monitored during startup operation after downtimes. However, exceptional boundary conditions, such as squeezing ground, improper conditioning, excessive tool wear, etc. are not accounted for in this research. Further research is required to estimate torque reserves under these circumstances.

Prediction results of large diameter project L are shown in Fig. 3 and compared to monitored values as well as installed nominal, exceptional and breakout main drive torque.

Fig. 3 shows that the installed torque matches the prediction range of the empirical approach, but that the monitored torque shows smaller values. The lines of maximum torque in Fig. 3 relate to:

breakout installed: maximum motor capacity installed for instant use only (impulse)

exceptional installed: maximum motor capacity installed, only for timely limited use (temporary)

nominal torque: motor capacity for normal operation (perpetual)

ML mean: torque prediction using machine learning model

ML max: maximum torque value using correlation

The ML approach results in a more accurate torque estimation range than the empirical approach. The following table shows the estimation accuracy for all three validation projects with a prediction improvement of up to 166 %, which is the difference between the delta of ML approach and empirical approach compared to the monitored torque.

It is important to mention that the main drive torque is depending on

Table 5
Model evaluation using 13 input features compared to 14 input features (including sum of injected liquids).

no. of input features	best performing ML algorithm	R^2	RMSE [MNm]	torque prediction [MNm]			
				project L	project G	project A	total error
optimum values		**1**	**0**	**25,93**	**6,86**	**2,49**	**0**
13 features	Bagged Tree Ensemble	0,96	1,93	26,10	8,77	2,81	2,39
14 features	Boosted Tree Ensemble	0,91	2,66	26,60	8,85	2,74	2,91

Table 6
Prediction improvement comparing monitored torque, ML approach and empirical approach.

project, diameter	approach	monitored torque [MNm]	ML approach [MNm]	Δ [%]	empirical approach [MNm]	Δ [%]	prediction improvement [%]
A:6,5 m	mean torque: a = 10	2,47	2,74	11 %	2,84	15 %	4 %
	maximum torque: a = 25, linear fit	4,99	4,07	−18 %	7,09	42 %	24 %
G:12,1 m	mean torque: a = 10	6,86	8,85	29 %	17,69	158 %	129 %
	maximum torque: a = 25, 95 % conf.	15,67	18,15	16 %	44,23	182 %	166 %
L:15,9 m	mean torque: a = 10	25,58	26,6	4 %	40,50	58 %	54 %
	maximum torque: a = 25, 95 % conf.	58,80	62,2	6 %	101,25	72 %	66 %

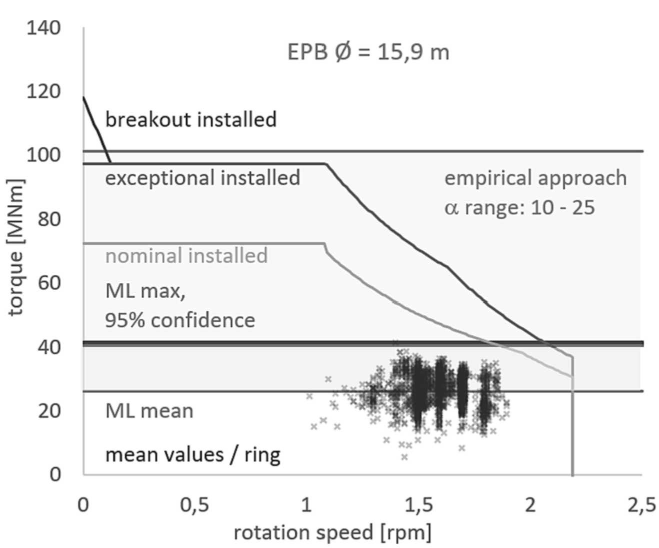

Fig. 3. Machine learning model validation for EPB reference project L with 15,9 m diameter.

numerous boundary conditions. The reference projects do not comprise exceptional boundary conditions, such as e.g., excessive tool wear or insufficient ground conditioning, unusual operational factors, such as exceeding rotation speed or thrust force as well as ground conditions, such as swelling or sticky ground. Hence, the presented ML approach and maximum torque correlations do not cover exceptional boundary conditions. Further research is required to improve prediction accuracy, especially for projects in such exceptional conditions.

4. Conclusions

In this study, the data of 9 reference projects has been used to train and test several machine learning algorithms for main drive torque prediction and the models have been validated using the data of 3 additional reference projects. The main conclusions and findings are summarized in the following:

(1) State-of-the art approaches return a wide range of torque estimations due to uncertainties regarding the empirical factor α for the empirical approach and the friction coefficient μ for the theoretical approach.
(2) Back calculated α values based on monitored mean and maximum torque per ring of the reference projects range between 4,8 and 12,1 for mean torque values and between 8,7 and 20,8 for maximum torque values.
(3) Tunneling data is prone to significant variance in data quality and the work with EPB tunnelling data revealed that the data is often unreliable and messy. Sensors might be soiled, blocked or uncalibrated and additional, unmonitored equipment might be installed on site misguiding and disorienting machine learning algorithms. Intense data engineering is required before using the data.
(4) In this context, robust machine learning models such as the boosted or bagged tree ensembles demonstrated to be suitable algorithms for TBM tunneling applications, while showing excellent model performance and prediction results. Another advantage is the transparent decision-making process of these algorithms. The bagged tree model returned best results for the manually selected input features with an R^2 of 0,96 and an RMSE of 1,9277. Prediction accuracy and utilization improved up to 166 %.
(5) Feature Selection Algorithms resulted in less accurate prediction results than manually selected input parameters known to have a causal relation to the target value.
(6) The results of this research showed that in cases where the machine learning model is trained and tested using data from various projects with comparable features (e.g., EPB TBM type in mixed ground), also cross-project predictions are possible, and the prediction models are transferable to future projects with comparable boundary conditions.

To further improve estimation results using machine learning approaches the focus should be improving the quality and quantity of the data base as well as the monitoring system of the influencing parameters before further optimizing the algorithms. It is essential to fortify statistics, data science and machine learning with real world causal nexus. Adding reference projects to enlarge the data base and range of training data could improve transferability and accuracy of the predictive model. Logic checks and redundant sensor systems could help to automatically check calibration of sensors and monitoring of important boundary conditions such as the characteristics of the ground can help to further improve predictions and the overall tunnelling process optimization. Further research is required to study the impact of certain factors such as e.g., the ground conditioning by improving the monitoring of the conditioning and using the data for further machine learning projects. Furthermore, exceptional boundary conditions, such as squeezing ground, excessive tool wear, etc. should be subject for further research. Increasing the database by adding the data of further comparable reference projects using EPB TBMs would be beneficial for the prediction accuracy as well as for the transferability of the model.

CRediT authorship contribution statement

K. Glab: Writing – original draft, Writing – review & editing, Visualization, Investigation, Formal analysis, Methodology. **G. Wehrmeyer:** Supervision. **M. Thewes:** Supervision. **W. Broere:** Supervision.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: co-author serving in an editorial capacity for the journal - W.B.

Data availability

The data that has been used is confidential.

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