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Energy Efficient EPB Design Applying Machine Learning Techniques

K. Glab[1], G. Wehrmeyer[1], M. Thewes[2] and W. Broere[3]
[1]*Department for Research and Development, Herrenknecht AG, Schwanau, Germany*
[2]*Institute for Tunnelling and Construction Management, Ruhr- University, Bochum, Germany*
[3]*Civil Engineering and Geosciences, Geo-Engineering, Technical University Delft, Netherlands*
E-mail: glab.kathrin@herrenknecht.de

ABSTRACT: A significant part of the energy consumed during the tunnelling process of Earth Pressure Balanced (EPB) Tunnel Boring Machines (TBMs) is related to the main drive, consisting of a set of motors driving the rotation of the cutting wheel. An energy efficient EPB design requires the optimization of the main drive to avoid over- or under powering of the machine. Key aspect is therefore a precise and reliable estimation of the expected cutting wheel torque. In this paper state-of-the-art torque estimation models are compared to supervised machine learning (ML) approaches, including classification and regression trees (CART), support vector machines (SVM), Gaussian process regression (GPR) and decision tree ensembles (DTE). Feature selection algorithms are compared to models using manually selected input features. ML models are evaluated using accuracy metrics, residual analyses, and model validation. Torque prediction for a real-world validation project shows that utilization rates can be increased distinctively due to the application of ML techniques.

KEYWORDS: EPB TBMs, energy efficiency, main drive utilization, torque estimation, supervised machine learning, feature selection

1. INTRODUCTION

The increasing demand to improve sustainability and energy efficiency of TBM tunnelling projects is currently challenging the tunnelling business. The TBM is one of the main assets on TBM tunnelling projects in terms of energy consumption, and it is therefore necessary to optimise the power consumption of the machine in the first place.

During the TBM design phase the main drive torque is estimated to determine the number of motors required to turn the cutting wheel and excavate the ground throughout the tunnelling process. This estimation is crucial since the machine must be equipped with sufficient power to prevent the TBM from getting slowed down or stuck in the ground. On the other hand, the main drive should not be overpowered to save energy and reduce costs for purchase, operation and maintenance of motors and gears.

Empirical and theoretical approaches to predict the main drive torque require input factors, which are difficult to estimate during the design phase of a TBM. This results in a wide range of torque estimation. To compensate this uncertainty and avoid torque related deceleration of the machine, safety margins are considered, frequently leading to an overpowering of the EPB main drive capacity. A reliable and accurate torque prediction facilitates the optimisation of the EPB main drive, improving the main drive utilization and energy efficiency of EPB TBMs. In this paper, a new torque estimation model is presented based on supervised ML techniques.

2. TORQUE PREDICTION AND UTILIZATION

An accurate prediction of the cutting wheel torque for EPB TBM design is challenging due to the large number of impact factors and reciprocal effects related to the active tunnel face support.

First, the configuration of cutting wheel and working chamber as well as the TBM operation is of importance. Torque values increase with cutting wheel size and thrust forces pushing the TBM forward. Closed cutting wheel structures elevate friction forces leading to higher torque components.

Second, the type of ground and its characteristics influence the amount of required main drive torque. Ground material with higher strength values for instance or cohesive ground with high clogging potential lead to increased torque values.

Standard approaches to estimate the main drive torque M_T are:

- empirical approach,
  using the TBM diameter D as input factor and an empirical factor α (Eq. (1)), accounting for all remaining torque influencing parameters

$$M_T = \alpha * D^3 \quad (1)$$

- theoretical approach,
  sum of separately calculated torque components T_i caused by ground excavation, friction between rotating steel structure and excavated ground material as well as shearing of the ground material due to the cutting wheel rotation (Eq. (2)). System inherent components such as friction losses at the bearing and sealing system are usually small and neglectable.

$$M_T = \sum T_i \quad (2)$$

The empirical approach has been published by (Krause, 1987) and slightly adapted by (JSCE, Japan Society of Civil Engineers, 2007) regarding the recommended range of the empirical factor α. (Krause, 1987) suggested α values between 12 and 24 whereas (JSCE, Japan Society of Civil Engineers, 2007) indorse α values ranging from 10 to 25.

(Shi, Yang, Gong, & Wang, 2011) used the theoretical approach and calculated 7 torque components to estimate the cutting wheel torque, whereas 4 components accounted for the friction between steel parts and ground material. To calculate these friction components, the authors use the friction coefficient μ. The values of the friction coefficient used in literature range between 0,14 to 0,73 (Song, Liu, & Guo, 2010).

Both input factors, the empirical factor α as well as the friction coefficient μ, are unknown during the design phase of an EPB TBM and vary throughout the tunnelling process. They depend not only on the specific geotechnical conditions and the pressure situation at the tunnel face but also on the excavation and muck conditioning process. However, both factors, α and μ, are of critical importance for the torque estimation. Figure 1 shows torque ranges using both estimation approaches compared to monitored mean and maximum values of an 8 m diameter EPB TBM.

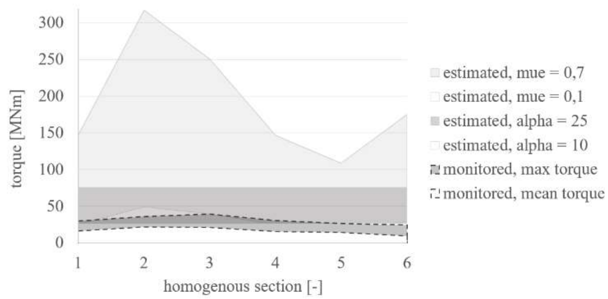


Figure 1 estimated and monitored main drive torque for 6 homogenous sections of an 8 m EPB drive

The torque estimation range increases with the size of the TBM and so does the level of uncertainty. Similar results have been published e.g. by (Shi, Yang, Gong, & Wang, 2011) for the α value and (Ates, Bilgin, & Copur, 2014) for the friction coefficient μ.
The analysis of monitored mean torque values per ring and installed nominal torque of completed EPB TBMs shows quite low average main drive torque utilization, ranging around 35% with significant potential for optimization (Figure 2).

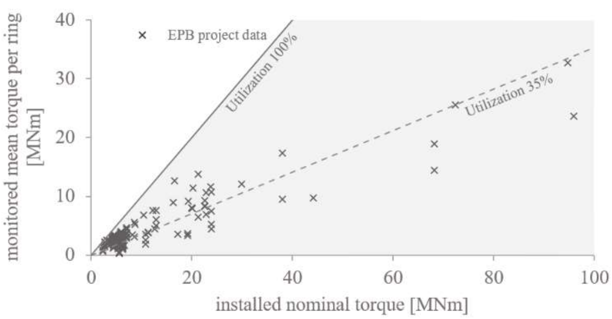


Figure 2 EPB Main Drive Torque Utilization

A new torque prediction approach is presented based on a ML approach to optimize the main drive capacity of EPB TBMs. Input parameters required for the torque prediction using the ML model should be measurable, well-established, and available during the design phase of a TBM.

3. METHODOLOGY

ML approaches have been increasingly used to forecast TBM process related parameters, like penetration or advance rate. Usually, the ML models are trained on the data of a single project (e.g. Mooney, Yu, Mokhtari, Zhang, & Zhou, 2018). As a result, the transferability to other projects with differing characteristics is limited.
The database utilized for this research shows a broad variance of input features. Model validation ensures that an accurate prediction is provided for new and unseen project data, as would be the case in a real-world design process.

3.1 Reference Projects and Data Preparation

The analysis of main drive torque utilization has been carried out based on the data of 231 completed EPB projects. 12 of these projects ranging from 7 m to 16 m diameter have been selected for the ML approach, mainly based on data quality and project range. The geotechnical conditions throughout the projects cover fine to medium grained soft ground as well as weathered to competent hard rock environments. 9 projects have been used to set up the prediction model, leaving 3 projects for model validation. In total 64 features (see Table 1 and 2) describe the characteristics of TBM design, geotechnical conditions, and TBM operation. Mean values per tunnel segment ring are used with geotechnical data being interpolated between boreholes. The database comprises a sample size of 16209 rings.

3.2 Feature Selection Algorithms (FSAs)

It is standard practise to reduce the number of input features for ML tasks as far as prediction accuracy is not impaired. Identifying the crucial impact factors is an important task in predictive modelling. In scope of this research, the following methods have been used:

- Spearman's coefficient of correlation
- Rrelief Algorithm
- Neighbourhood Component Analysis (NCA)

Spearman's coefficient of correlation describes the relationship between the respective input feature and the cutting wheel torque, which is used to select features with large correlations. Coefficients vary between -1 and +1.
RreliefF is a well-established algorithm for regression problems using k-nearest neighbours of an observation to assign weights between -1 and 1 and penalize input features in an iterative process.
NCA is based on the leave-one-out classification, where the function is trained on all parameters except one. The algorithm assigns 0 to irrelevant features.
The selected feature sets are then used as predictors for the ML algorithms and compared to manually selected features.

3.3 Machine Learning Algorithms

To develop a new approach of main drive torque prediction for EPB TBMs the following supervised ML techniques have been applied and evaluated:

- classification and regression trees (CART)
  using varying leave sizes (fine trees with 4 leaves, medium trees with 12 leaves and coarse leaves with 36 leaves)
- decision tree ensembles (DTE)
  applying boosted tree ensembles and bagged ensembles
- support vector machines (SVM)
  using linear, cubic, quadratic and Gaussian Kernel functions
- Gaussian process regression (GPR)
  applying squared exponential kernel, exponential kernel, matern 5/2 kernel and rational quadratic kernel as covariant functions

To reduce the risk of model overfitting 5 to 15-fold cross validation has been applied.

3.4 Model Evaluation

Main aspect of model evaluation is the accuracy of the prediction, which has been assessed using following common accuracy metrics:

- coefficient of determination R^2

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \tag{3}$$

  with the sum of squared deviations from predictive function SS_{res} and the sum of squared deviations from mean value SS_{tot}.
- root mean squared error RMSE
  the squared root of the sum of squared prediction errors

Another very useful evaluation tool is the analysis of the residuals, the differences between the monitored target values and the predicted values. Residuals should be evenly distributed over predictions, samples, target values, and input variables. In cases whit increased errors over specific sections, this might hint to missing features, where the selected input does not sufficiently describe the underlying causalities.
Model validation as third evaluation tool simulates a real-world design prediction of the cutting wheel torque. A 16 m diameter EPB project has been used to validate the models. The prediction results of the model validation give some indication on model transferability and show how well the model performs on unseen data.

4. RESULTS AND DISCUSSION

4.1 Feature Selection

The results of the FSAs are presented in Table 1 and 2. Threshold values for feature selection using Spearman's coefficient have been defined, with features being selected if correlation is larger +0,7 or smaller -0,7. This algorithm selects 13 features in total. 5 features are selected by the RreliefF algorithm with weights larger than 0,009 while using k=10 nearest neighbours for the algorithm. NCA identifies 7 features with major impact on the main drive torque. 13 features are selected manually.

Table 1 Feature Selection:
TBM design and geotechnical parameters

category	FSA method		Spearman	RreliefF k=10	NCA	manual
	no. features selected		13	5	7	13
TBM design	diameter	[m]	✓	-	-	✓
TBM design	degree of cutting wheel opening	[%]	-	-	-	✓
TBM design	no. of hard rock tools (disks)	[-]	-	-	-	-
TBM design	no. of soft ground tools (knife, ripper)	[-]	-	-	-	-
TBM design	no. of buckets	[-]	-	-	-	-
TBM design	no. of struts	[-]	✓	-	-	-
TBM design	no. of mixing bars	[-]	✓	-	-	-
TBM design	depth of tool gap and steel structure	[m]	-	-	-	-
TBM design	depth of working chamber	[m]	✓	-	-	-
TBM design	weight of cutting wheel	[t]	✓	-	-	-
TBM design	diameter of bearing	[m]	✓	-	-	-
TBM design	no. of sealings	[-]	✓	-	-	-
TBM design	no. of hydraulic motors	[-]	✓	-	-	-
TBM design	no. of electric motors	[-]	-	-	-	-
geotechnical parameters	c' - cohesion	[kPa]	-	-	-	✓
geotechnical parameters	φ' – inner friction angle	[°]	-	-	✓	✓
geotechnical parameters	UCS – unconfined compressive strength	[MPa]	-	-	-	✓
geotechnical parameters	w_l – liquid limit	[%]	-	-	-	-
geotechnical parameters	w_p – plastic limit	[%]	-	-	✓	-
geotechnical parameters	I_P – plasticity index	[%]	-	-	-	✓
geotechnical parameters	I_C – consistency index	[-]	-	-	-	✓
geotechnical parameters	W – natural water content	[%]	-	-	-	-
geotechnical parameters	RQD	[%]	-	-	-	-
geotechnical parameters	GSI	[-]	-	-	-	-
geotechnical parameters	cover above crown	[m]	-	-	-	-
geotechnical parameters	depth below ground water (crown)	[m]	-	-	-	-
geotechnical parameters	c_u – undrained shear strength	[kPa]	-	-	✓	-
geotechnical parameters	k_f - permeability	[m/s]	-	-	-	-
geotechnical parameters	SiO2 – quartzite fraction	[%]	-	-	-	-
geotechnical parameters	CAI - abrasivity	[-]	-	-	-	-

Table 1 summarizes the results for TBM design parameters and geotechnical parameters, Table 2 shows the results for TBM operational parameters and virtual sensors.

Table 3 lists the best performing ML algorithms for each FSA and compares the accuracy and residuals of these FSA- ML combinations.

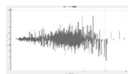
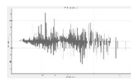
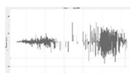
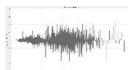
Table 2 Feature Selection:
TBM operation and virtual sensors

category	FSA method		Spearman	RreliefF k=10	NCA	manual
	no. features selected		13	5	7	13
TBM operation	main drive torque	[MNm]	-	-	-	-
TBM operation	rotation speed	[rpm]	✓	-	-	✓
TBM operation	penetration	[mm/rot]	-	✓	-	✓
TBM operation	advance speed	[mm/min]	-	✓	✓	-
TBM operation	thrust force	[kN]	✓	-	-	✓
TBM operation	temperature center plate	[°C]	-	-	-	-
TBM operation	FER – foam expansion ratio	[-]	-	✓	-	-
TBM operation	FIR – foam injection ratio	[%]	-	-	-	-
TBM operation	roll of shield (VMT)	[mm/m]	-	-	-	-
TBM operation	longitudinal inclination (VMT)	[mm/m]	-	-	✓	-
TBM operation	copy cutter, extending right	[°]	-	-	-	-
TBM operation	copy cutter, extending left	[°]	-	-	-	-
TBM operation	band scale 1	[t]	✓	-	-	-
TBM operation	band scale 2	[t]	-	-	-	-
TBM operation	rotation speed screw conveyor	[rpm]	-	✓	-	-
TBM operation	torque screw conveyor	[kNm]	✓	-	-	-
TBM operation	main drive current	[%]	-	✓	-	-
TBM operation	main drive torque [max/ring]	[MNm]	-	-	-	-
TBM operation	foam lines inner ring	[l]	-	-	-	-
TBM operation	foam lines outer ring	[l]	-	-	-	-
TBM operation	specific energy (PLC)	[MJ/m³]	-	-	✓	-
virtual sensors	geological category	[-]	-	-	-	-
virtual sensors	operation mode	[-]	-	-	-	-
virtual sensors	delta earth pressure crown previous ring	[bar]	-	-	✓	-
virtual sensors	mean earth pressure	[bar]	-	-	-	✓
virtual sensors	sum of foam injection	[l]	-	-	-	-
virtual sensors	sum water quantity	[l]	-	-	-	-
virtual sensors	sum of liquid injection (foam and water)	[l]	-	-	-	-
virtual sensors	specific energy	[MN/m²]	-	-	-	-
virtual sensors	apparent muck density crown	[kN/m²]	-	-	-	✓
virtual sensors	apparent muck density invert	[kN/m²]	-	-	-	✓
virtual sensors	sum polymer 1+2	[l]	✓	-	-	-
virtual sensors	sum greasing	[kg]	-	-	-	-
virtual sensors	sum bentonite	[l]	-	-	-	-

Spearman's correlation attaches most importance to TBM design values, neglecting geotechnical characteristics entirely. The RreliefF algorithm focusses solemnly on TBM operational parameters, whereas NCA neglects TBM design parameters. Both algorithms ignore for instance the important factor of the TBM diameter.

Algorithm based feature selection shows heterogenous results and neglects some principle causal interrelations.

Table 3 Evaluation of Feature Selection Models

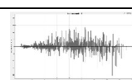
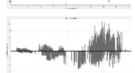
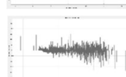
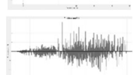
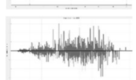
FSA	Best performing ML algorithm	R^2	RMSE	residuals vs. predicted response
target value	-	1	0	evenly distributed around 0-line
Spearman's Coefficient of Correlation	GPR, Rational Quadratic	0,94	0,27	
RreliefF	GPR, Rational Quadratic	0,93	0,22	
NCA	GPR, Rational Quadratic	0,95	0,232	
Manual Selection	*GPR, Exponential*	*0,96*	*0,188*	

Comparing the performing results of the different feature sets, the manual selection achieves the best model performance. Even though the residuals show slightly increased error for medium torque values, they are equally distributed around the 0-line. A heterogenous distribution as shown for NCA indicates that the selected input features do not fully represent the torque influencing parameters.

4.2 Predictive Machine Learning Modelling

Based on the FSA results, the manual feature selection has been used to set up the ML model. Performance evaluation of selected algorithms is summarized in Table (4).

Table 4 Performance Evaluation of Machine Learning Models

ML algorithms	R^2	RMSE	validation prediction [MNm]	validation prediction error [MNm]	residuals vs. predicted response
target value	1	0	25,93	0	evenly distributed around 0-line
Fine CART	0,95	2,285	26,30	0,37	
SVM, Linear	0,85	3,98	29,91	3,98	
SVM, Cubic	0,94	2,47	9,12	16,81	
Bagged DTE	*0,96*	*1,93*	*26,10*	*0,17*	
GPR, Exponential	0,96	1,98	24,83	1,1	

The performance evaluation shows that the bagged DTE achieved the most accurate prediction for the mean main drive torque per ring.
CART and DTE are robust ML algorithms, which are easy to interpret since all decisions are traceable. However, those algorithms are labelled to be less accurate than SVM, GPR, neural networks (NN) or deep learning (DL) algorithms. This conflict is often referred to as accuracy-interpretability trade off. CART and DTE models showed excellent results in terms of prediction accuracy while providing a transparent decision-making process, being a big plus compared to black box type of algorithms.
However, for TBM design purposes, the maximum main drive torque is more pertinent than the mean torque. Analysis of the monitored torque values per ring show a clear correlation between maximum torque M_{Tmax} and mean torque M_{Tmean}. The following correlation has been used to calculate M_{Tmax} [MNm] for model validation based on the predicted M_{Tmean} [MNm] (Equation 4):

$$M_{Tmax} = 6,3 + 1,3 * M_{Tmean} \tag{4}$$

This correlation applies for well maintained and operated machines only and projects with boundary conditions comparable to the reference projects. Excessive main drive torque e.g. due to squeezing ground conditions or inappropriate machine maintenance has not been considered in scope of this study.
Utilization analysis of the validation project shows that the installed nominal torque lies well within the range of the predicted torque using the empirical approach (marked as grey area in Figure 3).

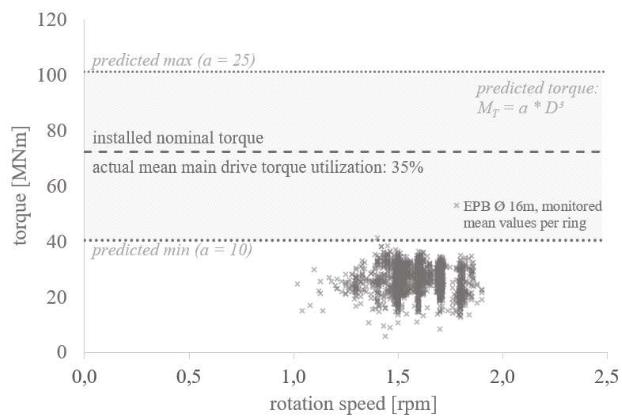


Figure 3 monitored TBM data compared to installed and predicted torque using the empirical approach

However, monitored values of torque and rotation speed are indicated as well, corresponding to an actual mean main drive torque utilization rate of only 35%.

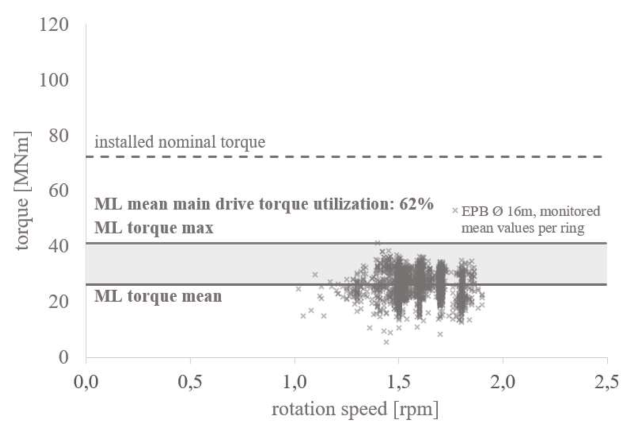


Figure 4 monitored TBM data compared to installed and predicted torque using the ML approach

Analysing the utilisation rate under application of the ML approach shows a distinct improvement from 35% to 62% of main drive torque utilization (Figure 4).

5. CONCLUSIONS

The application of feature selection algorithms did not improve prediction results compared to manually selected features. This might be caused by auto correlation and apparent correlation instead of physical causal relationships between input features and target value. Model evaluation demonstrates excellent prediction results, even for robust approaches. Especially decision tree ensembles seem capable to facilitate superior prediction results while providing a transparent decision process.

Value creation of machine learning tasks lies in the creation of the database in the first place. Yet TBM tunnelling data usually displays significant quality variation. Hence, robust decision tree ensembles might be a preferred solution in cases of limited data quality, when black-box type of algorithms suggest an accuracy, which is insubstantial due to the haziness of the underlying database.

Model validation proved transferability to real world design applications demonstrating an improvement of the main drive torque utilization from 35% to 62% for a 16 m EPB TBM. As a result, the energy efficiency of EPB TBMs can be improved using a machine learning approach to achieve more accurate torque predictions.

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