Descriptive statistical analysis of TBM performance at Abu Hamour Tunnel Phase I

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Abstract

The Abu Hamour Surface and Ground Water Drainage Tunnel Phase I is a 9.5-km-long, 3.7-m-inside-diameter storm water tunnel about 30 m below ground surface. Integral to phase I of the project are 19 access shafts on the tunnel line. The authors performed a rock mass quality assessment program combining borehole logging, shaft wall mapping, and laboratory testing. The results, including RMR and Q estimates, are presented and their relation to tunnel boring machine (TBM) performance examined. Rock mass properties and TBM operational data and charts are discussed. The paper also presents the results of a regression analysis linking the TBM penetration rate (PR) (mm/min) and field penetration index (FPI) (kN/cutter/mm/rev) with some geotechnical and operational parameters aggregated by strokes. For this purpose, simple, interpretable, and fairly strong general linear regression models were estimated. Then, a predictive neural network regression model was built and evaluated, revealing considerable predictive potential of the data.

Keywords EPB TBM · TBM performance · Penetration rate · Field penetration index · Multivariate regression · Neural networks

Introduction

Mechanical properties of rock and rock mass largely affect the penetration indices; therefore, they are commonly used in TBM performance evaluation (Yagiz 2008; Hassanpour et al. 2011; Delisio and Zhao 2014; Benato and Oreste 2015). Similarly, RMR, Q, and other rock mass quality ratings contribute to many TBM performance models (Bieniawski et al. 2007; Barton 2000; Hamidi et al. 2010; Hassanpour et al. 2016; Salimi et al. 2017; Maji and Theja 2017).

TBM data acquisition systems routinely collect steering and operational parameters for controlling and reporting purposes. Therefore, these data are also available for analyses and

empirical TBM performance models based on operational historical data and rock mass characteristics have been studied (Bruland 1998; Rostami et al. 2013; Jain et al. 2014; Maher 2017; Yagiz 2017).

TBM performance evaluations, specifically penetration indices, advance rates, and cutter wear, are the features most frequently explained and predicted with the empirical models. Example of different applications of TBM data analysis and modeling can be the evaluation of probabilities of occurrences and quantification of risks, project time, and cost (Grasso and Soldo 2017).

Earth pressure balance (EPB) TBM is an effective tunneling technology for a range of rock mass categories, and many successful project completions have been reported, including ones facing technological challenges (Chakeri et al. 2015; Moeinossadat et al. 2018). EPB TBM proved to be an adequate tunneling technology in post-Cretaceous marine limestone and shale formations in the Doha region encountered during the Abu Hamour tunnel project.

Authors have evaluated Q and RMR indices based on geological mapping of 19 shafts and logging 18 boreholes. Penetration was discussed in this paper as the function of rock mass properties and TBM tunneling operational features while progressing the 9.5-km-long Abu Hamour tunnel.

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Table 1 TBM specifications

Total length	124.5 m	Bore diameter	4.52 m
Weight	330 t	Cutterhead	Mixed
Core weight	172 t	Cutters	17
Curve radius	300 m	Scrapers	75
Gradient	0.05%	Buckets	8
UCS	2–65 MPa	Cutterhead speed	0–4.5 min ⁻¹
Hydrostatic pressure	2 bars	Nominal torque	2167 kNm
Segments per ring	6 + key	Maximum thrust	20,891 kN
Total rings installed	7198	Screw conveyor diameter	600 mm
Ring width	1.3 m	Segment backfill	Bi-component cement grout
Segment thickness	250 mm		

In an earlier study, authors have used general linear regression (GLR) and classification and regression tree (CART) regression models to investigate relations explaining TBM penetration indices with some geotechnical and operational parameters (Jakubowski et al. 2017). Then, authors have built and validated a predictive model coupling both GLR and CART models. The resultant model appeared robust and stronger than constituent ones.

In this paper, authors present general linear regression models explaining penetration rate (PR) and field penetration index (FPI) with some operational and geotechnical features. Furthermore, a predictive neural network regression model of PR was also trained and validated.

Project overview

The tunnel excavation was carried out by two TBMs with rotating cutterheads that were fitted with cutting wheels and cutting tools (buckets and slab cutters). The excavated material was collected by the “buckets” and transported through the openings provided between the cutters into the excavation chamber. A screw conveyor extracted the spoil from the chamber and discharged it onto the belt conveyor installed on the TBM back, which in turn offloaded the material into muck skips. The muck skips (a total of 26) were operated by diesel-powered locomotives (a total of 7) that traveled

Fig. 1 Interpreted geology from shaft mapping (both scales in m)

Fig. 2 Q and RMR correlation from relogging (blue triangles) and shaft wall mapping (brown squares) at the tunneling horizon. Eastern and western drives combined

on the tunnel rail track. The permanent lining of the tunnel consists of dowelled, pre-cast concrete segments reinforced with steel fibers. See Table 1 for additional details. Monitoring of the TBM excavation processes was provided in real time by Herrenknecht-made operation and guidance systems. The drive data were automatically collected by the TBM data acquisition and evaluation system.

The 19 access shafts are mostly drop shafts that facilitate runoff inflows along the route of the tunnel. The tunnel runs from the existing access shaft AS23 to a retrieving shaft located within the footprint of a future pumping station at the coastline to be constructed in phase II of the project. Access shaft AS11, a launching shaft centralized along the alignment, was used to launch two tunnel boring machines mining in opposite directions, providing access for tunnel construction. Two shafts

Table 3 Overall production performance (6 days a week, 2×11 h shifts)

	TBM west	TBM east
Start of production run	5/13/2014	7/7/2014
Breakthrough	7/22/2015	7/29/2015
Production calendar days	436	388
Production work days	302	281
Best week (meter/week)	144	168
Best day (meter/day)	30	35
Average work days (meter/day)	15	17
Average calendar days (meter/day)	12	14
Best week (ring/day)	19	21
Best day (ring/day)	23	27
Average work days (ring/day)	12	13
Average calendar days (ring/day)	9	11
Total project utilization	69%	72%

10 m in diameter were intended as the TBM reception shafts at each end of the project: AS22R and the PS-TBM recovery shaft, located inside the future pump station footprint.

The project was completed under budget and ahead of schedule. The owner (or employer), PWA-ASHGHAL, was the designated engineer represented by CDM Smith. The CDM Smith design team provided engineering design review, verification, and approval services for all the designs produced by the contractor's team. CDM Smith was also the construction manager on this project. For more information related to the project, please refer to Stypulkowski et al. (2014), Stypulkowski and Bernardeau (2018), and Pathak et al. (2015).

Table 2 Statistical summary of input parameters and classification results

Classification system parameters/results	Original assessment, median	Relogging, median	Shaft mapping, median	
			From	To
RQD	55	37.3	40	50
Joint number	6	20	20	15
Joint roughness	3	4	3	4
Joint alteration	3	4	2	3
joint water	0.66	0.66	0.5	0.66
Q	1.232	0.58	0.792	2
Rating for UCS	2	2	1	2
Rating for RQD	13	8	3	8
Rating for spacing of discontinuities	5	8	5	8
Rating for condition of discontinuities	9	10	0	10
Ground water rating	10	7	7	10
RMR	34	37	18	38

Table 4 TBM operation and performance statistics based on strokes

	TBM west	TBM east
Tunneling time (min)	35	30
Liner erection time (min)	27	22
Stop time (min)	42	36
Penetration rate (m/h)	2.4	2.8
Cutterhead torque (kNm)	1226	1149
Thrust force per cutter (kN)	382	341

Geology

The project area is geologically a part of the Arabian Gulf Basin. It forms a part of the Arabian shelf between the Arabian shield and the Iranian mobile belt. The thickness of sediments in the Qatar region is estimated to be approximately 10 km (Abu Zeid 1991; LeBlanc 2008). The post-Cretaceous sedimentation is basically a sequence of shallow marine limestone with occasional shale and evaporates in a shallow basin. The formations encountered in the Doha region comprise Quaternary marine, eolian, and sabkha deposits; Rus of Lower Eocene, Lower Dammam, and Upper Dammam of Middle Eocene and Lower Dam of Lower Miocene. As shown in Fig. 1, we encountered the following rock domains listed from the ground surface down: Simsima Limestone, which contains Dolomite of the Upper Dammam formation, Midra Shale of the Lower Dammam formation, and Rus of Lower Eocene, is below Midra.

An integral part of supervision of the field activities is observation of the rock as it is exposed during excavation. Using shielded TBMs with segmental lining prevented continuous geological mapping. The rock mass was therefore properly surveyed only at all shaft locations spaced

approximately 500 m apart. The objective of the wall mapping program was to establish the large-scale rock mass characteristics by geotechnical observations (Q, RMR) of the exposed rock face. Midra was encountered at different elevations along the alignment. Visually, the most distinguishing feature between Simsima and Midra was the change in color. However, there is also a gradational change: Simsima is sandy-silty, whereas Midra is silty-clayey. Based on shaft mapping, we reinterpreted and further subdivided Midra into two categories, which we called Light Buff Midra overlying Dark Buff Midra. They are compositionally, structurally, and strength wise different from each other, with sharp contacts. The thickness of layers varied from 2 cm to 1.5 m. The strength varied from medium strong rock to weak rock and from very weak rock to extremely weak rock. The silty/sandy limestone comprises only 34% of the total composition, while clay-rich components comprise 66% at the tunneling horizons of the shaft junctions. Mapping procedures and results have been described in detail in Pathak et al. (2015).

Rock and rock mass properties

Laboratory tests were conducted on rock samples obtained from borings before construction. Uniaxial compressive strength (UCS) test results ranged from 2 to 65 MPa (median 15 MPa). The tensile strength from Brazilian tests ranged from 0.1 to 9.1 MPa (median 1.7 MPa). The Is(50) from point load testing ranged from 0.03 to 7.5 MPa (median 1.3 MPa). Young's modulus from UCS testing ranged from 0.4 to 49 GPa (median 4.2 GPa). The pressure-meter testing results in the initial loading ranged from 79 to 5.31 GPa (median 0.39 GPa) while the down-hole seismic test results ranged from 1 to 4.3 GPa (median 2.4 GPa).

Fig. 3 Pressures recorded during tunneling

Fig. 4 Ground water pumped directly to the TBM for both drives

Sample preparation for weak rock materials is more difficult compared to that for hard rock materials. Often, methods of sample preparation and laboratory testing for weak rocks are similar to those for soils. It has been reported (Stypulkowski et al. 2014) that it is often hard to obtain a sufficient number of samples with an L/D ratio larger than 2, as the drilling program into weak rock is usually difficult. This also leads to a collection of the best samples for testing and not necessarily representative ones.

The calculated correlation between Q and RMR results are shown in Fig. 2 and are similar to those presented in the literature. The mapping process results and analyses have been described in detail by Pathak et al. (2015) and are summarized in Table 2. Predictably, the original assessment compared with the shaft mapping results was generally conservative. Mapping results, compared with relogging of the available shaft borings, were generally optimistic.

Limited laboratory testing of the muck was conducted. The test results indicate that the clay contents varied between 23

and 35%, silt contents from 9 to 16%, PI from 57 to 36%, and LL 10 to 130%. Eastern samples with 56% sand and/or gravel and 44% silty clay limit plot as silt of high plasticity and elastic silt (MH) and are classified as clayey sand (SC) or clayey gravel (GC) in a unified system. Western samples with 61% sand and/or gravel and 39% silty clay limit plot as MH and are classified as SC or GC in the unified system as well.

Summary of TBM performance

Simple analysis of the data from the TBM data acquisition and evaluation system provided in predefined reports has been performed. Key data from the production drives for both TBMs in terms of the best/average performance and TBM utilization are shown in Table 3. Significant differences in the TBM cutterhead torque and thrust force per cutter were noted between the drives, and both were lower for the eastern drive. The eastern drive was faster and more efficient than the

Fig. 5 Thrust force (left) and torque (right) vs. penetration per revolution (PPR) (mm/rev) for the eastern drive

Fig. 6 UCS vs. FPI (left) and UCS vs. penetration rate (PR) (right) in shaft areas

western drive. Statistics of the TBM advance and erection times per stroke are shown in Table 4. The stop time of the western drive is significantly higher, indicating perhaps a systematic lower efficiency.

Based on the assessment of the ground conditions to be encountered during the TBM drives, a plan for advance of tunnel was prepared ahead of the tunneling, and tentative values for the face pressure to be maintained along the tunnel alignment at the TBMs were defined. It was anticipated that the TBM drives will require, for most of this project, a face pressure lower than the in situ earth pressure at rest, as the ground formations to be crossed were expected to be stable. The actual TBM operation mode was decided based on the preference of the TBM operator and the behavior of the TBM backfill grout. The total amount of air pumped into the chambers for both drives indicated that both TBMs were operated in semi-closed modes for most of the drives. The piezometric head in the work chamber was established based on the water level measured in borings during the investigation phase. If water was truly present, it would have had a destabilizing effect. According to Fig. 3, pressures recorded during tunneling did not reach the anticipated level until the station at approximately 7500 m. The piezometric levels recorded in the boreholes suggest that two aquifers were most likely present and likely breached during the piezometer installation, which led to incorrect water pressure estimates. There were no issues observed with face stability during interventions at the face in the free air.

To provide the desired consistency of the muck for most of the drive, additional ground water had to be pumped in with surfactants diluted by service water. As shown in Fig. 4,

significant quantities of water were required for all the drives in an aquifer below the layer of the Dark Buff Midra. Ground water volumes did not show any clear relationship with penetration rates.

TBM penetration considerations

The authors looked at scatter plots for the torque (kNm) and thrust per cutter (kN) vs. penetration per revolution (mm/rev). As shown in Fig. 5, no change of penetration can be associated with thrust and torque increases typically observed in hard rock. This kind of behavior has been observed in highly fractured rock by Avunduk et al. (2012).

The relationships of UCS with the penetration rate, torque, and thrust for access shafts are shown in Figs. 6 and 7.

Performance estimations with the use of empirical formulas

It is expected that factors impacting penetration rates in soft ground will be different than those in hard rock for the EPB TBM. Penetration in hard rock is linked to rock hardness, etc., while soil conditioning determines the penetration rates in soft ground. The TBM performance prediction models for hard rock have been described in detail in Hassanpour et al. (2011). Maher, in his online article, suggested that there is a relationship between penetration and surfactants used in soft ground. In this paper, the authors examine the applicability of both approaches in weak/soft rocks of Doha.

Fig. 7 UCS vs. torque (left) and UCS vs. total thrust (right) in shaft areas

Fig. 8 Field penetration index at shaft locations for both drives

The latest trend in TBM performance estimations using empirical models often relies on historical field data for various ground conditions. The authors used formulas published in Hassanpour et al. (2011) to estimate the FPI from selected parameters (UCS, RQD, RMR, Q) and compared it with an average of 50 strokes obtained from the vicinity of the shafts. The results are presented in Figs. 8 and 9. Correlations appear to be weak. Estimated FPI rates were significantly lower than actual rates. It can therefore be concluded that hard rock approach in FPI predictions cannot be used in weak/soft rocks of Doha without adjustments.

Statistical models for penetration

To search for relationships between penetration rate and some TBM operational and geological parameters, a further analysis of the data acquired during tunneling was performed. The processed dataset of 6882 cases was aggregated by TBM strokes. The investigated dependent variables were penetration rate (PR) (mm/min) and field penetration index (FPI) (kN/cutter/mm/rev). Two groups of independent variables were considered: TBM operational (specifically, steering parameters) and geological data. Operational parameters (such as

steering and surfactant consumption) are adjusted, automatically or manually, in response to the change of tunneling conditions and performance. In effect, they impact TBM performance and may be dependent on the performance and other conditions at the same time. Parameters showing a direct relation to PR (such as muck weight or injected grouting volume) were eliminated from the analysis.

In contrast to predictive models and analysis, the goal of the explanatory regression analysis was to search and describe simple relationships between PR and a set of explanatory variables. Therefore, the method selected for building the model should be interpretable and the set of independent variables possibly small. For this purpose, general linear regression (GLR) was employed. Technically, it was a generalized linear model (GLM) with an identity link function and a normally distributed response. Variable selection, initially supported by semi-automated selection methods, was completed manually. Among the over 100 explanatory variables considered for the analysis, a narrow set of continuous and categorical variables was selected for the models. The correlation table for the continuous variables is presented in Table 5.

All models presented below meet respective statistical model assumptions and are statistically significant. All independent variables in the models are statistically significant.

Fig. 9 Scatterplots of FPI from 50 TBM strokes at shaft locations vs. FPI predicted from UCS, RQD, RMR, and Q based on shaft mapping. FPI (kN/cutter/mm/rev)

Table 5 Linear correlation coefficients for dependent and independent variables used in models. Values in brackets mark variables not included in the respective PR or FPI model

	Explanatory continuous variables 6882 cases (strokes)	Pearson's correlation	
		Penetration rate (PR)	Field penetration index (FPI)
1	Torque avg	−0.15	(0.25)
2	Thrust avg	−0.43	(0.63)
3	Torque*rotation max	−0.47	(0.59)
4	Torque/thrust avg	0.28	(−0.35)
5	Jacking force invert/crown	0.21	−0.26
6	Vol. of water pumped directly	−0.37	0.11
7	Overburden to tunnel crown	−0.17	0.02
8	UCS	−0.53	0.34
9	Surfactant consumption	(−0.22)	−0.02

The number of cases is large compared to the number of dependent variables used in the models. To evaluate the fit of the multidimensional regression models, a model response vs. observation plot was employed to calculate Pearson's correlation and determination coefficient R^2 . This was considered sufficient for descriptive models, but would probably not be if predictive models were involved.

As mentioned before, a significant difference in PR values for eastern and western drives was observed (Fig. 10, left). Categorical variable drive was employed in the models, labeling the western or eastern part of the tunnel. Penetration rates are also differentiated by strata formations (see an example in Fig. 10, right). Geological strata formations through which the tunnel is driven, from the elevation of crown, axis, and invert locations, were identified along the tunnel length. These formations were interpolated from available core drills and the mapping of nearby shafts. Simplifying the geological strata, three types of Simsima, one of Midra Shale, and one of Rus were used to describe strata formations in crown, axis, and invert. Then, this information was coded in a categorical variable, strata. A substantial number of UCS tests for each of the

geological formations were performed, so the average UCS in the tunnel face was further used in the models as the discriminator variable of strata properties.

First, a linear model explaining the penetration rate PR with TBM steering and geological parameters was built. The model included two categorical and eight continuous variables: drive, strata, torque avg (kNm), thrust avg (kN), torque*rotation max (kNm/min), torque/thrust avg (m), jacking force in invert to jacking force in crown ratio, total volume of water pumped directly (l), overburden to tunnel crown (m), and average UCS in the tunnel face (MPa). Model summaries and model responses vs. observations scatter plots are presented in Table 6 and Fig. 11. The correlation coefficient exceeds 0.8, with more than 65% variability explained by the model. A further reduction in the number of variables is still possible with a small decrease in R^2 . Taking into consideration the simple linearity of the model, relatively low number of variables (even with dummies coding categorical data), low resolution of geological data, and need for interpolation over large distances, the explanatory capability of this model is quite high.

Fig. 10 Penetration rate (PR) (mm/min) discriminated significantly by drive (left) and by crown strata formation (right)

Table 6 Summary of regression models

No.	Dependent variable	Explanatory (independent) variables	R	R^2	Figure number
1.	Penetration rate (PR) (mm/min) GLR model	- Drive - Strata - Overburden - UCS - Torque avg - Thrust avg - Torque*rotation max - Torque/thrust avg - Jacking force invert/crown - Volume of water pumped	0.81	0.65	Fig. 11
2.	Field penetration index (FPI) (transformed) GLR model	- Drive - Strata - Overburden - UCS - Jacking force invert/crown - Volume of water pumped - Surfactant consumption	0.71	0.50	Fig. 12
3.	Penetration rate (PR) (mm/min) Neural network model	- Drive - Strata - Overburden - UCS - Torque avg - Thrust avg - Torque*rotation max - Torque/thrust avg - Jacking force invert/crown - Volume of water pumped	0.91	0.82	Fig. 13

Fig. 11 GLR model of penetration rate PR (mm/min) explained by operational and geological variables. Scatterplot of model response vs. observations. See Table 6, model 1

Fig. 12 GLR model of transformed FPI explained by operational and geological variables. Scatterplot of model response vs. observations. See Table 6, model 2

A regression model for the field penetration index FPI (kN/cutter/mm/rev) was also investigated. FPI and PR have generally opposite correlations with individual explanatory variables (see Table 5). From the earlier considered variables, all variables involving thrust and rotation were excluded to avoid direct dependencies. Additionally, torque (kNm) was excluded. Since FPI observations are not normally distributed, a Box-Cox transformation was applied before further processing. The regression result is presented in Table 6, showing an R of 0.71 and an R^2 of 0.50. Compared to the previous PR model, the FPI model does not include four TBM steering variables and shows good performance regardless. A respective scatterplot (Fig. 12) shows some vertical groups of points,

indicating the importance of categorical variables in this model. Due to this and to a slight narrowing of the range of the dependent variable, the model could have limited applications in prediction models but appears to be satisfactory for indicating significant and relatively strong relations between variables.

Finally, a neural network model was built to illustrate our further research toward the implementation of predictive models for the considered data. A set of 25 MLP neurons, a BFGS learning algorithm, an SOS error, and a logistic neuron activation function were used to build the neural network model. An evaluation of the model based on validation sample showed $R = 0.91$ and $R^2 = 0.82$, which proves the solid

Fig. 13 Neural network model of penetration rate PR (mm/min). Scatterplot of model response vs. observations (mm/min) for validation sample. See Table 6, model 3

predictive capabilities of the data (see Table 6 and Fig. 13). There is also a potential to use GLR and GLZ to improve the models' performances both toward explaining and predicting.

Summary

The authors created a comprehensive geotechnical database on the tunneling project in weak/soft rocks, which has been compared with operational data collected by the TBMs. Since geotechnical investigations were conducted largely around the shafts located along the alignment, the TBM data were delineated to areas around the shafts. At this time, it has been concluded that FPI predictions using hard rock models for rock mass commonly found in Doha would underestimate actual penetration rates.

To search for relationships between penetration rates and some TBM operational and geological parameters, further statistical analysis of the acquired data was performed. Despite complexity of the phenomena and interactions accompanying the process of EPB TBM tunneling, the high variability of the operational data, the low resolution of geological data, the need for interpolation, and the weak correlations between TBM advance performance and individual independent variables, the outcome appeared promising. General linear regression analysis showed fairly strong and significant relationships between PR, FPI, and the investigated parameters. A neural network regression model revealed considerable predictive potential of the dataset.

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