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Data-driven Model for Predicting Surface Settlement in response to Tunnel Boring Machine Excavation

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ABSTRACT

The effective management of surface settlement induced by tunnel boring machine (TBM) excavation is crucial for mitigating potential casualties and structural damage. As a TBM advances, the surface settlement undergoes variations, highlighting the importance of continuous monitoring. However, conventional studies face challenges in addressing the extensive variations in surface settlement. To overcome this, this study proposes a data-driven model for predicting surface settlement in response to TBM excavation, using a database corresponding to seven days of excavation near each settlement measurement point. The optimal model was developed based on the Random Forest framework, achieving a RMSE of 0.962 mm and a R^2 of 0.913. Furthermore, the results of model interpretation demonstrated that the preceding settlement had a dominant influence on the prediction of subsequent settlement, followed by the cover depth of each settlement measurement point and TBM face pressure. The developed model can facilitate the adjustment of TBM operating conditions corresponding to encountered geological formations, thereby ensuring the effective management of surface settlement during TBM excavation.

1. INTRODUCTION

Recently, Tunnel Boring Machines (TBMs) have been widely utilized in tunnel construction owing to their eco-friendliness, stability, and constructability (Hyun et al., 2015). However, TBM excavation can cause surface settlement, leading to potential casualties and structural damage. Therefore, effective management of surface settlement in TBM tunnel projects is essential.

The longitudinal settlement profile at the ground surface exhibits dynamic variations during TBM tunnelling (Sugiyama et al., 1999). Remarkably, a substantial

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portion (approximately 70 %) of the total settlement, which reaches a constant value after a long-term period, can occur until promptly after the passage of the TBM shield (Fargnoli et al., 2013). However, few studies have focused on predicting the extensive variations in surface settlement, which depend on the distance between the TBM and measurement points. Analyzing these variations facilitates the examination of the immediate impact of adjusting operating conditions on surface settlement during TBM excavation, thereby proactively minimizing potential risks.

The machine learning approach may surpass analytical and numerical methods, primarily due to its capacity to effectively address complex and non-linear relationships among various features, along with its data-driven nature that avoids making assumptions. Therefore, this study developed a data-driven model to predict surface settlement variations in response to a slurry shield TBM advance. In addition, the developed model was interpreted to analyze the influence of each feature on surface settlement prediction.

2. Background

2.1 Random Forest (RF)

Random Forest (RF) is a widely used ensemble learning algorithm in machine learning that involves the bagging process. It creates multiple decision trees, each trained on a randomly selected subset (i.e., bootstrap sample) of the training data with replacement. During the prediction phase, individual trees trained by each bootstrap sample independently generate predictions, and the final prediction is determined through majority voting (in classification) or averaging (in regression). This approach helps to reduce overfitting and enhances the overall performance and robustness of the model.

2.2 SHapley Additive exPlanations (SHAP)

SHapley Additive exPlanations (SHAP) has emerged as a prominent algorithm in machine learning for addressing the interpretability challenge presented by black-box models. It is rooted in cooperative game theory, specifically the concept of Shapley values, which quantifies the average marginal contribution of each feature across all possible coalitions (Nordin et al., 2023). By applying Shapley values in machine learning, the SHAP algorithm can assess the impact of each feature on the model's prediction, thereby providing valuable insights into the decision-making process of the model.

3. Database

3.1 Site overview

This study focused on twin-bored tunnels, referred to as up-track and down-track tunnels (L=850 m), in Hong Kong, which were excavated using a slurry shield TBM, as reported in Kim et al. (2022). The specific details of the slurry shield TBM used are presented in Table 1. The geological formation of the site primarily consisted of five ground types: fill, alluvium, completely decomposed granite (CDG), core stone zone, and highly decomposed granite (HDG). The longitudinal geological profile of the site is illustrated in Fig. 1.

Table 1. Specifications of utilized slurry shield TBM

Description	**Specification**
TBM excavation diameter	7.4 m
Maximum thrust force	47,897 kN
Maximum torque	5 MN·m
Segment diameter	7.1 m (OD), 6.5 m (ID)
Segment width	1.5 m

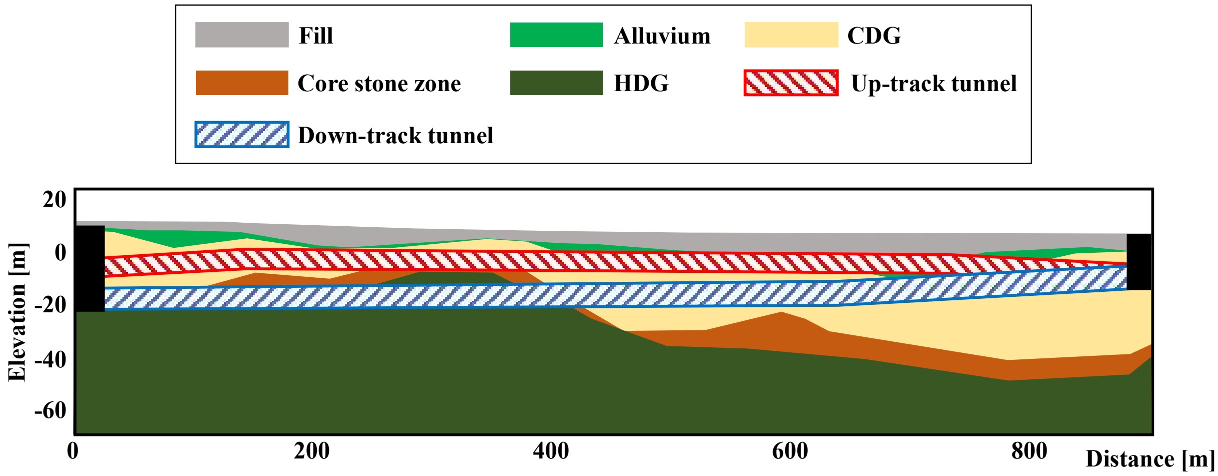


Fig. 1 Longitudinal geological profile of the site

3.2 Data pre-processing

The objective of this study is to predict surface settlement in response to TBM advance. To achieve this, it is crucial to determine the influence range within which TBM excavation can affect the magnitude of surface settlement at a designated settlement measurement point (i.e., target point). Kavvadas et al. (2017) observed that the surface settlement was relatively steady when excavating the ground outside a 5D distance ahead and behind the target point, where D represents the TBM excavation diameter. In this site's case, the TBM had a diameter of 7.4 m, and excavation proceeded at an average rate of 12 m per day. Accordingly, the influence range was defined as the sections excavated in proximity to each target point for seven days. This involved one day for excavating the ground beneath each target point and three days each for excavating the ground ahead and behind each target point.

The database comprised 14 features in four categories based on the influence range. Geometry features included the TBM location and horizontal distance. The TBM location indicated the position of the ring in excavation relative to the nearest target point in the tunnel axis direction, where - and + indicated the backward and forward directions. The horizontal distance represented the distance from the tunnel axis to each target point. Geology features included the standard penetration test (SPT) N-value, groundwater level (GWL), and cover depth at the TBM face, as well as GWL and cover depth associated with the ring located beneath each target point. TBM operation features consisted of the thrust force, torque, face pressure, advance speed, backfill grouting volume, and time, where the time referred to the elapsed time from excavating the first ring in each influence range, including the TBM suspension period. Lastly, settlement features were composed of preceding and current settlements, indicating the magnitude of surface settlement associated with excavating the previous and current rings, respectively. Statistical descriptions of the established database are summarized in Table 2. Data of all features, excluding those related to each target point (i.e., Horizontal distance, Target_GWL, and Target_cover depth in Table 2), were aggregated daily to align with the daily measurements of surface settlement.

Table 2. Statistical descriptions of the database

Category	Feature	Min	Q_1	Mean	Q_3	Max	COV*	Unit
Geometry	TBM location	-7.5	-4.5	0	4.5	7.5	–	m
	Horizontal distance	-18.52	-4.18	-3.27	0.30	18.24	-4.5	m
Geology	N-value	21	22	31	32	46	0.2	–
	GWL	0.8	1.7	2	2.4	2.7	0.3	m
	Cover depth	6.8	7.1	7.3	7.7	12.6	0.1	m
	Target_GWL	0.8	1.7	2	2.4	2.6	0.3	m
	Target_cover depth	6.8	7.1	7.3	7.6	9.9	0.1	m
Operation	Thrust force	11.8	13.4	15.6	20.8	27.2	0.2	MN
	Torque	0.35	0.69	0.99	1.25	1.63	0.3	MN·m
	Face pressure	1.39	1.55	1.91	2.16	2.35	0.2	bar
	Advance speed	11.80	17.67	27.73	35.71	44.21	0.4	mm/min
	Grouting volume	5.99	6.38	6.43	6.48	6.90	0.0	m^3
	Time	1	4	7	11	41	1.0	day
Settlement	Preceding settlement	-12.4	-4.8	-2.4	-0.7	3.2	-1.2	mm
	Current settlement	-12.4	-5.0	-2.4	-0.6	4.0	-1.2	mm

* Coefficient of variation

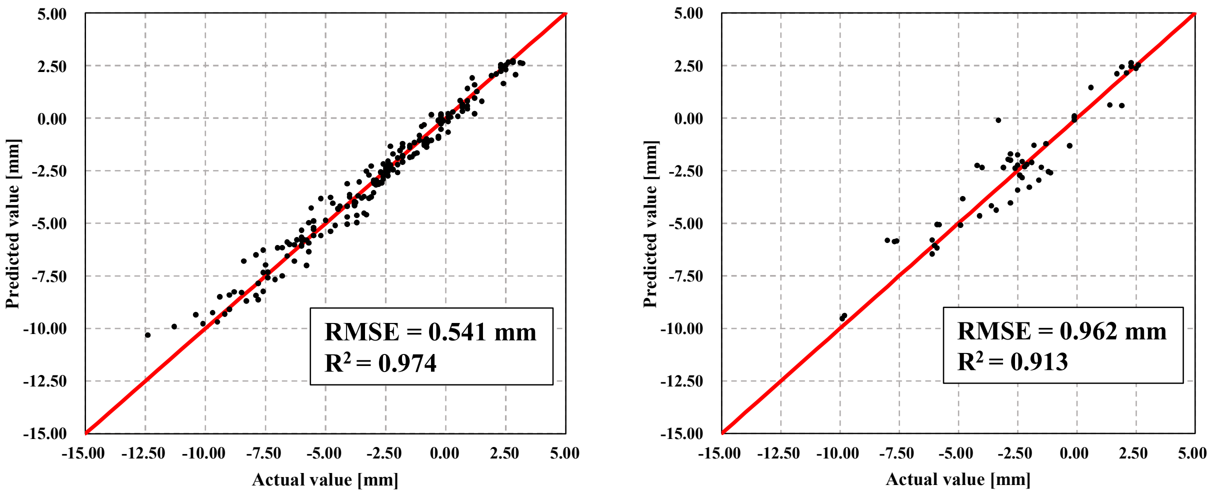
4. Method and Results

4.1 Model implementation

This study developed a predictive model for surface settlement in response to TBM excavation using the RF framework with the established database. This model was trained on 70% of the database (191 data points), and the remaining 30% (82 data points) was used for testing. Bayesian optimization coupled with a 5-fold cross-validation was employed for hyperparameter tuning. The prediction performance was assessed using the root mean squared error (RMSE) and the coefficient of determination (R^2).

4.2 Prediction performance

Fig. 2 presents the evaluated performance of the optimal predictive model, demonstrating satisfactory prediction capabilities in both the training and test phases. Specifically, the training phase yielded an RMSE of 0.541 mm and an R^2 of 0.974. During the test phase, the optimal model achieved an RMSE of 0.962 mm and an R^2 of 0.913. The hyperparameters selected for the optimal model were as follows: max_depth=17, min_samples_leaf=1, min_samples_split=8, and n_estimators=147.



(a) Training (b) Test

Fig. 2 Prediction performance for the optimal RF model

4.3 Model interpretation

The SHAP algorithm was employed to comprehensively analyze the contribution of each feature to the predictions of the optimal model. The analysis revealed that the preceding settlement had the most significant contribution to predicting the subsequent settlement, which was the focus of this study. Additionally, the cover depth of each target point and the applied TBM face pressure exhibited the second and third highest SHAP values, respectively. This finding suggests that shallow cover depth allows the ground deformation induced TBM excavation to easily propagate to the ground surface, and the ratio of face pressure to the overburden pressure is closely related to surface settlement.

In general, the features associated with the operation and geology of each target point demonstrated relatively higher SHAP values compared to other features. This highlights the importance of adjusting operating conditions appropriately and conducting thorough investigations into the geological properties of risky locations. In contrast, geological characteristics at the TBM face had little contribution to the model's outcome. This could be due to the operation features inherently encompassing the geology features at the TBM face, or the geological formations encountered along the tunnel alignment in this study being relatively consistent. The corresponding SHAP values for each input feature are illustrated in Fig. 3.

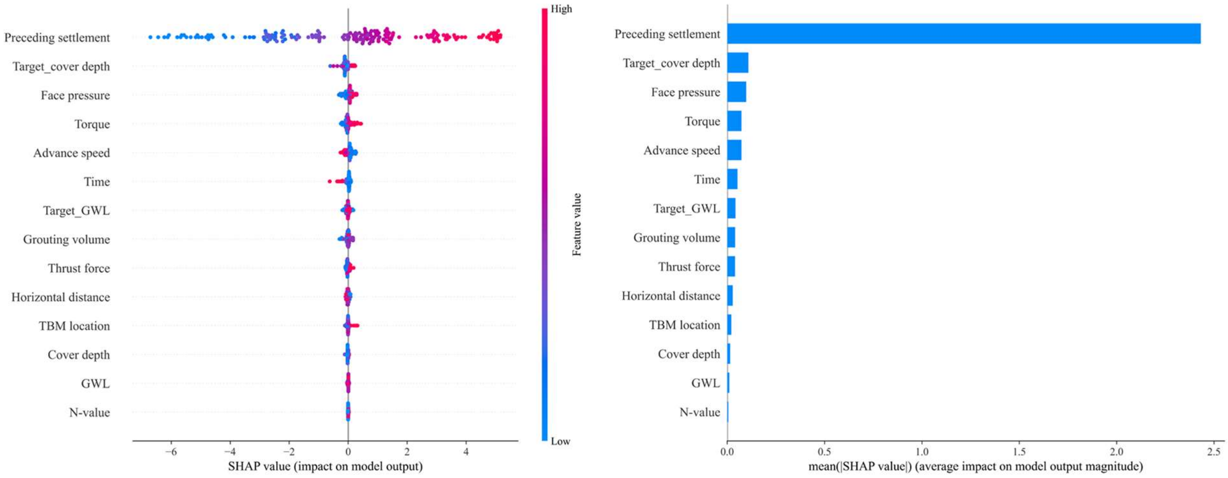


Fig. 3 Contribution of each feature on predictions of the optimal RF model

5. CONCLUSIONS

This study proposed a data-driven model for predicting surface settlement in response to TBM excavation. The predictive model was developed using the RF framework and a slurry shield TBM database consisting of 14 features. To enhance model interpretability, the SHAP algorithm was employed to analyze the contribution of each feature to the model's predictions. The key findings and contributions are as follows.

1) The optimal RF model demonstrated satisfactory prediction performance in both the training phase (RMSE: 0.541 mm, R^2: 0.974) and the test phase (RMSE: 0.962 mm, R^2: 0.913).
2) Model interpretation revealed that the preceding settlement played a dominant role in the predictions of the optimal RF model. Additionally, the cover depth of each settlement measurement point and TBM face pressure also exerted significant influences. In contrast, the geology characteristics at the TBM face had little contribution to the model’s prediction.
3) In practical applications, the proposed model can serve as an effective tool for mitigating and monitoring surface settlements during TBM tunnelling, thereby enhancing the safety and efficiency of the TBM tunnel projects.

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REFERENCES

Hyun, K. C., Min, S., Choi, H., Park, J., and Lee, I. M. (2015), “Risk analysis using fault-tree analysis (FTA) and analytic hierarchy process (AHP) applicable to shield TBM tunnels”, *Tunn. Undergr. Space Technol.,* **49**, 121-129.

Sugiyama, T., Hagiwara, T., Nomoto, T., Nomoto, M., Ano, Y., Mair, R. J., Bolton, M.D., and Soga, K. (1999), “Observations of ground movements during tunnel construction by slurry shield method at the Docklands Light Railway Lewisham Extension-East London”, Soils Found., **39(3)**, 99-112.

Fargnoli, V., Boldini, D., and Amorosi, A. (2013), “TBM tunnelling-induced settlements in coarse-grained soils: The case of the new Milan underground line 5”, *Tunn. Undergr. Space Technol.,* **38**, 336-347.

Kim, D., Kwon, K., Pham, K., Oh, J. Y., and Choi, H. (2022), “Surface settlement prediction for urban tunneling using machine learning algorithms with Bayesian optimization”, *Autom. Constr.*, **140**.

Nordin, N., Zainol, Z., Noor, M. H. M., and Chan, L. F. (2023), “An explainable predictive model for suicide attempt risk using an ensemble learning and Shapley Additive Explanations (SHAP) approach”, *Asian J. Psychiatry.,* **79**.

Kavvadas, M., Litsas, D., Vazaios, I., and Fortsakis, P. (2017), “Development of a 3D finite element model for shield EPB tunnelling”, *Tunn. Undergr. Space Technol.,* **65**, 22-34.