The 2021 World Congress on
Advances in Structural Engineering and Mechanics (ASEM21)
GECE, Seoul, Korea, August 23-26, 2021

Surface settlement prediction of stacked twin TBM tunnels by various machine-learning techniques

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ABSTRACT

Prediction of surface settlement during TBM tunnelling is a key design factor for urban tunnel excavation. The conventional prediction methods are not suitable for estimating surface settlement in urban areas, which are affected by numerous factors such as shallow ground depth, existing underground infrastructures, and disturbance from surface traffic. In this study, various machine learning (ML) models were explored to predict the maximum surface settlement using the extensive settlement database collected from a Hong Kong subway tunnel site. The optimal ML model was selected by comparing the root mean squared error (RMSE). The highest prediction performance was achieved with the extreme gradient boosting algorithm, which resulted in an RMSE of 1.989.

1. INTRODUCTION

Subway tunnel construction in urban areas became a challenging task due to an increase in infrastructure density. Deformation at the ground surface should be cautiously monitored at various risky locations along the tunnels to ensure safe and economic excavation. Current practices for predicting surface settlement employ numerical analyses because of complex excavation conditions in urban areas (Comodromos, Papadopoulou, & Konstantinidis, 2014; Ercelebi, Copur, & Ocak, 2011; Jallow, Ou, & Lim, 2019; K. Kim, Oh, Lee, Kim, & Choi, 2018; Lambrughi, Medina Rodríguez, & Castellanza,

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2012). However, the numerical analysis results are often limited, providing predictions at critical excavation conditions due to high computational cost. In addition, only the representative geotechnical parameters and geometrical conditions are employed for the analysis, with losing the opportunity to get full advantage of extensive data collected from real tunnel excavation sites.

In recent days, machine learning (ML) based settlement prediction methods have been suggested to predict the surface settlements induced by TBM excavation (Bouayad & Emeriault, 2017; C. Y. Kim et al., 2001; Mahmoodzadeh et al., 2020; Santos & Celestino, 2008; Suwansawat & Einstein, 2006). Unlike the numerical analysis method, the ML models consider all of the settlement influencing factors obtained from the construction site, which shows a highly complex inter-relationship. As abundant data are routinely collected from tunnel excavation sites, the ML models are expected to predict surface settlement accurately.

In this study, the surface settlement was predicted using the settlement database collected from a subway tunnel site in Hong Kong. Five different ML models are implemented to compare the prediction performance. The hyperparameters of each model are tuned using a grid search model and validated with the k-fold cross-validation method. The performance of models was evaluated with the root mean squared error to find the optimal ML model.

2. DATABASE

2.1 Tunnel site

Surface settlement monitoring data and excavation records were collected from a twin-tunnel subway construction site in Hong Kong, which allowed to develop the surface settlement predicting ML models. The 850-m-long tunnels were excavated using two slurry shield TBMs, with the outer segment diameter of 7.1m. The tunnel alignments have gradually changed from the laterally parallel twin-tunnel to the stacked twin-tunnel configuration along the tunnel chainage due to the densely populated urban construction condition. The up-track tunnel was excavated after the completion of the down-track tunnel in a relatively shallow depth ranging between 6.7 – 12.8 m. The geologic profile along the tunnel alignment consists of four strata, i.e., fill, alluvium, completely decomposed granite and corestone zone. The corestone zone is a discontinuous rock slab, which is encountered within the completely decomposed granite layer. The surface settlements were monitored daily at 253 locations along the tunnel alignment. The final settlement measurements were recorded 20 days after the up-track tunnel TBM passage.

2.2 Settlement influencing factors

A list of 42 settlement influencing factors employed for the implementation of ML models is summarized in Table 1. The factors are divided into four categories: geometry, TBM operation, geology and urban feature.

Table 1. List of settlement influencing factors

Category	Settlement influence factors	Unit
Geometry	Tunnel chainage *	m
	Tunnel depth *	m

	Tunnel horizontal distance	m
	Tunnel vertical distance	m
	Horizontal distance of monitoring location	m
TBM Operation	Face pressure *	bar
	Thrust force *	kN
	Cutter torque *	MN·m
	Backfill grout injection volume *	m^3
	Advance speed *	mm/min
	Net excavation time *	min
	Pitching *	mm
	Rolling *	mm
Geology	Ground water level	mPD**
	SPT N-value *	-
	Soil thickness above UT (Fill, Alluvium, CDG)	M
	Soil thickness above DT (Fill, Alluvium, CDG, Corestone, Rock)	m
	Soil type at crown, axis & invert *	Categorical
Urban feature	Building surcharge *	kN/m^2

* Data collected from both the up-track tunnel and down-track tunnel in this study
** mPD is the unit of ground depth representing the principal datum practiced in Hong Kong, i.e., 1.23m beneath the average tide levels in Victoria Harbour.

3. METHODOLOGY

3.1 Multi-layer Perceptron Regression

Multi-layer perceptron (MLP) is a supervised learning algorithm that belongs to the feedforward neural network. The MLP consists of three layers of calculation nodes, i.e., an input layer, a hidden layer and an output layer. In MLP, the input signals are transmitted towards the output layer by calculating weights and bias in each layer. The training process of the MLP utilizes a backpropagation technique, in which the weights and bias are updated to minimize the gradient of the loss function errors at the output layer. In this study, the sizes of the hidden layer, activation function, alpha (L2 regularization to avoid overfitting by penalizing weights) and maximum iteration number were tuned during the hyperparameter tuning process.

3.2 Support Vector Machine Regression

The objective of support vector machine (SVM) is to find a hyperplane in the multi-dimensional space that classifies data with the maximum margin. The support vector indicates the data points that are closest to the hyperplane. The SVM is a nonparametric ML model that utilizes kernel functions. The kernel functions transform input data into higher dimensional space, where the data points can be classified more accurately. In this study, the kernel function, c (regularization penalty parameter), epsilon (margin of tolerance with no penalty) and gamma (distance of data considered) were tuned during the hyperparameter tuning process.

3.3 Random Forest Regression

Random forest (RF) is an ensemble learning method consisted of multiple decision trees that utilize the bootstrap and aggregation (bagging) technique. The bagging process selects the training set from random sample sets with replacement, and aggregates the prediction results from multiple decision tree models. The hyperparameters of the RF explored in this study included the maximum depth of decision trees, minimum samples of leaf, minimum samples of split, and number of estimators.

3.4 Gradient boosting algorithms

Similar to the RF algorithm, the gradient boosting algorithms are one of the ensemble learning methods constructed from the decision tree models. In the gradient boosting algorithms, multiple weak decision trees provide sequential predictions, where new learners provide slightly improved prediction by calculating the largest residuals in the training data rows. Three boosting algorithms are employed for the prediction: Gradient boosting, Extreme Gradient Boosting (XGB) and Light Gradient Boosting Machine (LGBM). The searched hyperparameters include the number of estimators, learning rate, maximum depth, minimum child weight, sampling ratio of data (*subsample*), sampling ratio within columns (*colsample_bytree*), L1 norm (*alpha*), and L2 norm (l*ambda*).

3.5 Model implementation

For the implementation of the ML models, the surface settlement data were divided into the training set (80% of total data) and the test set (20% of total data). Before the ML model implementation, the data were scaled using the standard scaler to eliminate the effect of unbalanced distribution. As a result, the distribution of both training and test data was transformed to have the mean of zero and unit variance. The grid search method was employed for the hyperparameter tuning process of the ML models, where the best combinations of hyperparameters were selected from the search space shown in Table 2. The training process of each ML model was validated using the k-fold cross-validation method (k=5). The performance of the ML models is evaluated by calculating the root mean squared errors (RMSE) using Eq. (1).

$$RMSE=\sqrt{\sum_{i=1}^{n}\frac{\left(Predicted_i-Actual_i\right)^2}{n}} \tag{1}$$

Table 2. Search space of hyperparameters

ML Algorithm	Hyperparameters	Search space [range]
MLP	*hidden_layer_sizes*	[1,100] – [1, 100] – [1, 100]
	activation	[‘relu’, ‘tanh’, ‘logistic’]
	alpha	[1e-3, 0.5]
	solver	['adam', 'lbfgs', 'sgd']
	max_iter	[100, 1500]
SVM	*kernel*	[‘rbf’, ‘poly’, ‘sigmoid]
	gamma	[1e-4, 1]

	epsilon	[1e-4, 1]
	c	[1, 10000]
RF	*max_depth*	[2, 100]
	min_samples_leaf	[1, 10]
	min_samples_split	[2, 10]
	n_estimators	[10, 1000]
Gradient Boosting / LGBM / XGB	*n_estimators*	[200, 1500]
	learning_rate	[0.01, 0.1
	max_depth	[5,15]
	min_child_weight	[0, 10]
	subsample	[0.6, 1]
	colsample_bytree	[0.6, 1]
	reg_alpha	[1e-5, 100]
	reg_lamba	[1e-5, 100]

4. RESULT

The prediction performance of the ML models using the tuned hyperparameters is shown in Fig. 1. Most of the ML models in consideration measured acceptable performance with high precision considering the range of the monitored surface settlements, i.e., between -17.2 and 4.1 mm. The XGB regression model showed the highest prediction accuracy with the RMSE of 1.989. On the other hand, the lowest prediction accuracy was observed in the multi-layer perceptron regression model, which scored the RMSE of 3.115.

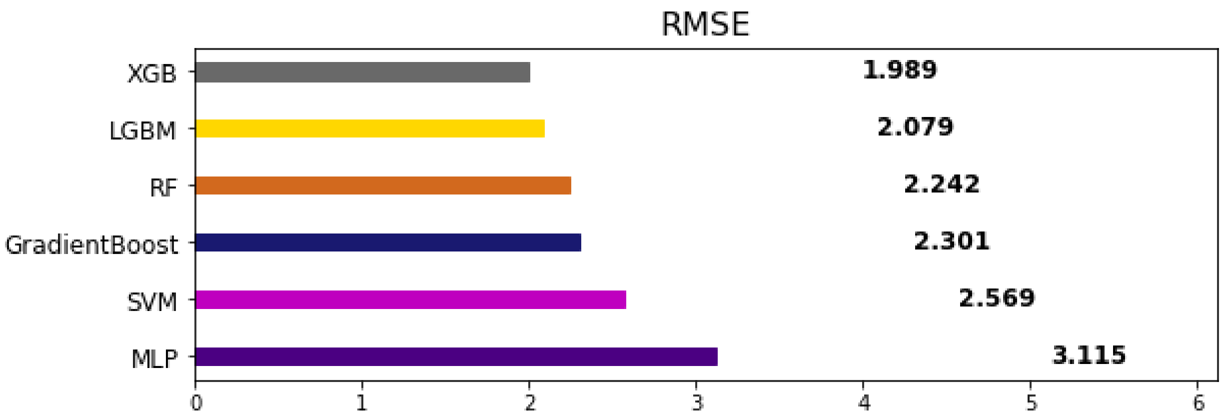

Fig. 1 Prediction performance of the tuned ML models

5. CONCLUSION

This study investigated various ML regression models to estimate the surface settlements monitored from a shield TBM tunnelling site in an urban area. The ML models were implemented with the database of settlement influencing factors, consisting of 42 factors collected from both twin-tunnels. The highest prediction accuracy was obtained in case of the XGB algorithm, which scored the RMSE of 1.989. Consequently, the ML models are strongly suggested to be utilized as a prediction method for surface settlement in urban tunnel excavation sites, which are often complicated due to surrounding conditions.

ACKNOWLEDGMENTS

This research was conducted with the support of the "National R&D Project for Smart Construction Technology (No.21SMIP-A158708-02)" funded by the Korea Agency for Infrastructure Technology Advancement under the Ministry of Land, Infrastructure and Transport, and managed by the Korea Expressway Corporation.

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