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Prediction of maximum surface settlement caused by earth pressure balance shield tunneling using random forest

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Abstract
Underground tunneling for the development of underground railway lines as a rapid, clean, and efficient way to transport passengers in megacities has received a great deal of attention. Since such tunnels are generally excavated beneath important structures in urban zones, estimating the surface settlement caused by tunnel excavation is an important task. During the recent decades, many attempts have been made to investigate the influencing factors affecting the amount of surface settlement. In this study, random forest (RF) is introduced and investigated for the prediction of maximum surface settlement (MSS) caused by earth pressure balance (EPB) shield tunneling. The results obtained show that RF is a reliable technique for estimating MSS using the geometrical, geological, and shield operational parameters. The applicability and accuracy of RF, as a novel approach, is checked by comparing the results obtained with the artificial neural network (ANN), as a popular artificial intelligence algorithm. The proposed RF model shows a better performance than ANN.

Keywords: *Tunnel, Earth Pressure Balance (EPB), Maximum Surface Settlement (MSS), Random Forest (RF).*

1. Introduction
This Underground transportation such as subway is a rapid, clean, and efficient way to transport passengers in the developing countries. Underground tunneling for the development of such infrastructures is a complex process since it may cause a serious damage to the existing structures owing to a partial settlement. Therefore, forecasting the ground behavior and surface settlements during excavation is a vital task that can be estimated using empirical [1-5], analytical [6-11], and numerical methods [12-15]. Indeed, the amount of maximum surface settlement (MSS) is a complex function of many geotechnical and geometrical parameters. Since the empirical and analytical approaches have mostly been developed on the basis of some simplifying assumptions, such methods generally fail to consider all the relevant factors that jointly affect the settlement, and thus a more comprehensive attempt is required for estimating the surface settlement caused by tunnel excavation. The artificial intelligence (AI)-based methods have the capability to be used in the problems with a huge number of factors possibly involved for modeling the complex relationships between the inputs and outputs or find patterns in the available data. AI-based methods are usually known as powerful tools for classification and prediction [16]. These methods such as the artificial neural network (ANN) [15, 17, 18], wavelet network (Wavenet) [19], support vector machine (SVM) [20], and wavelet smooth relevance vector machine (wsRVM) [21] have been used for analyzing the settlements caused by tunnel excavations during the past decade. The procedure used by the AI-based methods essentially involves training a model using a training data set that contains all shield operational records and field instrumentation readings. The training stage is required to include the inherent highly non-linear and multi-dimensional relationship between the settlement and the influencing factors.

In this work, a new approach is proposed for the prediction of MSS of tunnels using random forests

(RFs). RF is an ensemble learning technique developed by Breiman [22] based on a combination of a large set of decision trees. In the last decade, there has been a growing trend in the use of decision tree algorithms for modeling and approximation of complex non-linear systems. The tree growing algorithm used in RF is a kind of classification and regression tree. A decision tree partitions the input space of a data set into mutually exclusive regions, each of which is assigned a label (classification tree) or a value to characterize its data points (regression tree) [23, 24]. Decision trees are rather sensitive to small perturbations in the learning set. This problem can be mitigated by applying bagging (**B**ootstrap **agg**regat**ing**) [25]. RF is a combination of the random sub-space method proposed by Ho [26] and bagging.

RFs in both the classifier and regression forms have been successfully applied to a large number of problems including classification of hyper-spectral data [27], prediction of bird distributions and mammal species characteristic to the eastern slopes of the central Andes [28], prediction of long disordered regions in protein sequences [29], classification of agricultural practices based on Landsat satellite imagery [30], classification of electronic tongue data [31], prediction of building ages from LiDAR data [32], and many others. Recently, RF has been applied to predict the liquefaction potential of soil using the CPT data, and has demonstrated a considerable degree of success [33]. However, to the best of the knowledge of the authors, RF has not been used for estimating MSS caused by EPB shield tunneling.

2. Materials and method

2.1 Random forest

Random Forest (RF), as a relatively new pattern recognition method, has been proposed by Breiman [22]. It uses a kind of learning strategy called ensemble learning that generates many predictors and averages the outputs as shown schematically in figure 1, where i is the number of trees in RF, and $(S_{max})_1$, $(S_{max})_2$, and $(S_{max})_i$ are the output trees. Each tree is trained by selecting a random set of variables and a random sample from the total dataset. RF is not very sensitive to its parameters, and works just based on the number of trees ($ntree$) and number of variables in the random subset at each node ($mtry$). Therefore, SF is very user-friendly and easy to use approach for classification, regression, and unsupervised learning [34].

Since, in this investigation, the response variable is the value for maximum settlement, S_{max}, the regression form of RF is of particular interest. The main regression RF steps can be summarized as follows (for more details, the readers are referred to Breiman [22]):

(1) The $ntree$ bootstrap samples X_i (i = bootstrap iteration) are randomly drawn with replacement from the original dataset, each containing approximately two-third of the elements of the original dataset X (in our case, approximately 33 elements out of 49 ones). The elements not included in X_i are called the out-of-bag (OOB) data for that bootstrap sample.

(2) For each bootstrap sample X_i, an unpruned regression tree is grown. At each node, rather than choosing the best split among all predictors, as done in classic regression trees, the $mtry$ variables are randomly selected, and the best split is chosen among them.

(3) The OOB data is predicted by averaging the predictions of the $ntree$ trees, as explained below. The OOB elements are used to estimate an error rate, called the OOB estimate of the error rate (ERR_{OBB}), as follows:

i. At each bootstrap iteration, the OOB elements are predicted by the tree grown using the bootstrap samples X_i.
ii. For the ith element (y_i) of the training data set X, all the trees are considered, in which the ith element is OOB. On average, each element of X is OOB in one-third of the $ntree$ iterations. On the basis of the random trees, an aggregated prediction g_{OOB} is developed. The OOB estimate of the error rate is computed as:

$$ERR_{OOB} = (1/ntree)\sum_{i=1}^{ntree}\left[y_i - g_{OOB}(X_i)\right]^2 \qquad (1)$$

ERR_{OOB} helps prevent over-fitting, and can also be used to choose optimal values for $ntree$ and $mtry$ by selecting the $ntree$ and $mtry$ values that minimize ERR_{OOB}. Therefore, we first chose the optimal values for $ntree$ and $mtry$ that minimize ERR_{OOB}, and then proceeded to develop the RF model. As ERR_{OOB} is an unbiased estimate of the generalization error; in general, it is not necessary to test the predictive ability of the model on an external data set [22].

2.2. Case study

In order to show the capabilities of utilizing RF for predicting the MSS caused by an earth pressure balance machine (EPB) shield tunneling, the reported field measurements of Bangkok subway project were utilized. Figure 2 shows a schematic view of the apparatus used for the EPB shield tunneling. EPB, as a safe, rapid, and routine excavation technique, which is popular for tunnel construction, was used for the first phase of an integrated transportation plan for Bangkok, operated by Mass Rapid Transit Authority (MRTA), which is a governmental agency under the ministry of transportation in Thailand. Bangkok lies in the Chao Praya delta plain. Its topography is low and flat, varying approximately in the range of 0.5-1 m above the mean sea level.

This research work was performed based on a unique and comprehensive EPB tunneling database of Bangkok subway project that contained monitoring results of operational records and field instrumentation readings [35]. For a more detailed information, the readers are referred to Suwansawat [35].

3. Factors affecting surface settlements

The results of a literature review [15, 20, 21, 36-38] showed that the main factors influencing settlement in EPBM tunneling can be categorized into (1) tunnel geometry, (2) geological conditions, and (3) shield operation factors. Statistical characteristics of the data used in this work are summarized in table 1. This dataset consisted of 49 data that had been previously used by Suwasawat [15] and Pourtaghi [19]. Each category of the data used is defined and described in the following sub-sections.

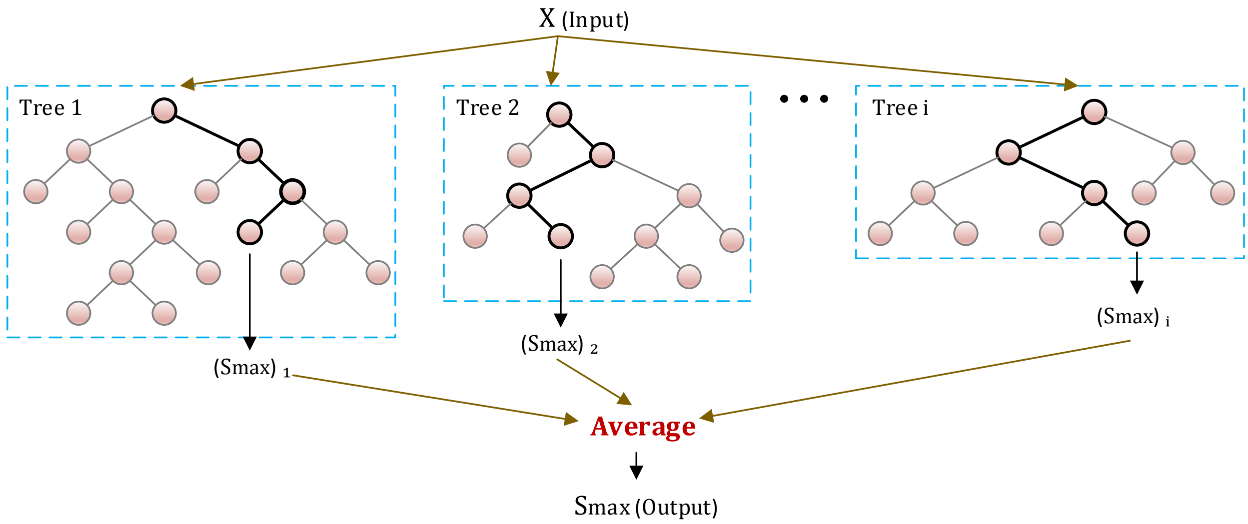
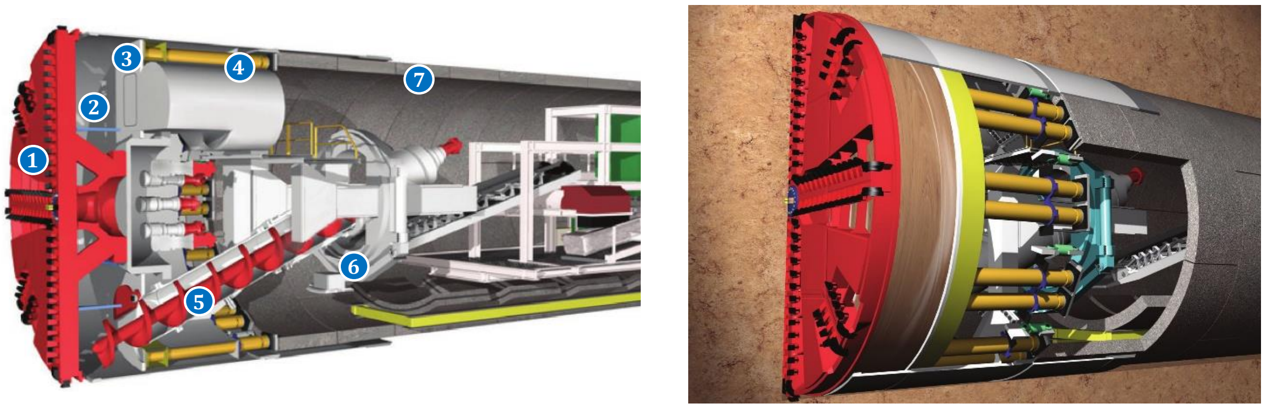


Figure 1. A general architecture of an RF for S_{max} prediction.



Legend: (1) Cutter head; (2) excavation chamber; (3) bulkhead; (4) thrust cylinders; (5) screw conveyor; (6) segment erector; and (7) segmental lining.

Figure 2. Overview of EPB [47].

Table 1. Statistical Characteristic of data used in this study.

Category	Parameters		Count	Minimum	Maximum	Mean	StdDev[b]
Tunnel geometry	Tunnel depth (m)			17.89	24.82	22.05	1.93
	Distance from shaft (m)			33.60	3055.20	1320.27	969.50
Geological conditions	Geology at crown [a]	Soft clay	1	-	-	-	-
		Stiff clay	48				
	At invert	Stiff clay	29	-	-	-	-
		Sand	20				
	Invert to WT (m)			-5.97	0.96	3.20	1.93
EPBM operation factors	Face pressure (kPa)			14.50	131.00	54.73	28.62
	Penetrate rate (mm/min)			20.10	76.85	42.63	12.87
	Pitching angle (°)			-1.38	1.43	0.05	0.83
	Tail void grouting pressure (kPa)			230.00	740.00	278.14	91.56
	Percent of tail void grout filling (%)			70.00	224.00	125.96	27.29

[a] Soil types at tunnel crown and invert are binary data.

[b] StdDev refers to the standard deviation.

3.1. Geometric characteristics

Depth and diameter of tunnels are the most geometrical parameters affecting the amount of settlements. However, since the entire length of the Bangkok subway project had a constant diameter of 6.30 m, the effect of tunnel diameter was negligible in this case study. In this regard, the tunnel depth is the most important geometric factor. The distance from the launching station, as defined in figure 3, is another influencing factor included in this study.

3.2. Geological conditions

Since a detailed geological investigation of the soil properties at the instrumentation sections was practically impossible, it was difficult to obtain the values for the soil properties. However, the Young's modulus and shear strength are the soil properties that have been taken into consideration as the geological factors by some investigators [39, 40]. Soil type is a good indicator and a major factor involved in determining the settlement. Kim, Bae [41], Suwansawat and Einstein [15], and Wang, Gou [21] have used soil type to represent the soil properties. In the model presented in this paper, the soil types at the tunnel crown and at the tunnel invert were considered as two geologic factors. Ground water level from the tunnel invert was another geological parameter included.

3.3. EPBM shield operation factors

In EPBM tunneling, shield is operated by controlling the amount of excavated material transported from the face by a screw conveyor. Therefore, the tunnel face could be supported by the material held in the excavation chamber at a controlled pressure. In practice, face pressure in the chamber plays a crucial role in maintaining stability of the excavation and minimizing settlements. Therefore, it is one of the most significant factors that have a direct effect on the magnitude of surface settlements. Considering many research works, applying low face pressures would cause large settlements, and vice versa. [12, 15, 36, 42-44].

The penetration rate measures how fast the shield can move forward (mm/min), and it is typically measured in every excavation cycle. It seems that the penetration rate affects the surface settlements. In practice, to achieve an earth pressure balance mode, shield operators have to control the rate of spoil extraction to correspond to the penetration rate. If the extraction rate is too high, compared to the penetration rate, it means that the shield excavates too much volume of soil relative to the volume replaced by the advancing shield. As a result, the excavated volume of the soil becomes unbalanced with the volume of soil that is occupied by the shield advance so that ground loss would be expected. On the other hand, if the extraction rate is too low, compared to the penetration rate, it means that the excavation volume is less than the volume replaced by the shield advance. As a result, the shield may generate a too high face pressure [35].

The pitching angle reflects the shield position, which has to be kept within the designed alignment. However, it is practically impossible to maintain an accurate orientation along the entire length of the tunnel. The mismatch between the actual position and the designed alignment may influence the settlement because it can create voids, as depicted in Fig. 4.

The quality of the tail void grouting also contributes to the extent of the ground settlement. As the shield is jacked forward, a tail void around the outside of the lining is created, as shown in Fig. 5. Tail void grouting is necessary to prevent ground moving towards the void. In general, the grouting pressure should be high enough to guarantee the flow of grout material, and to resist the ground moving into the void. Another criterion to check the grouting performance is the percent of grout filling, which has to be maintained at a level higher than the theoretical void [15]. Tunneling operations with a high grouting pressure and a high percent of grout filling can reduce considerably the settlements developed after the shield passing [35, 45]. In summary, five factors, namely, face pressure, penetration rate, pitching angle, tail void grout pressure, and grout filling were considered as the shield operational parameters in the model presented in this paper.

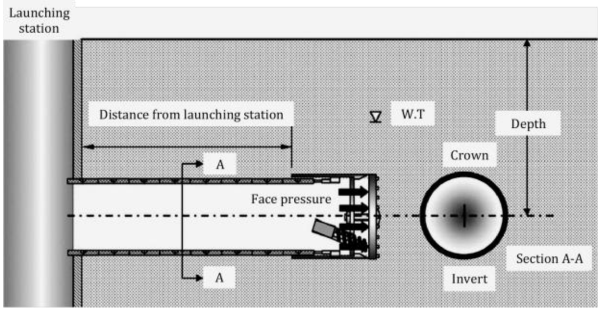


Figure 3. Geological and geometry parameters [15].

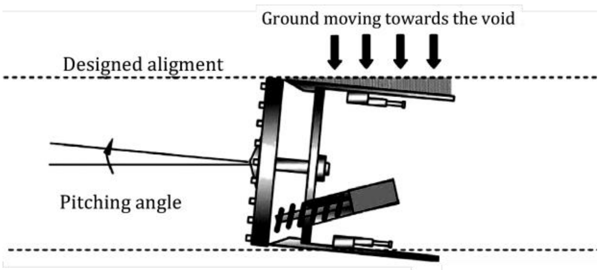


Figure 4. Ground movement caused by pitching angle [15].

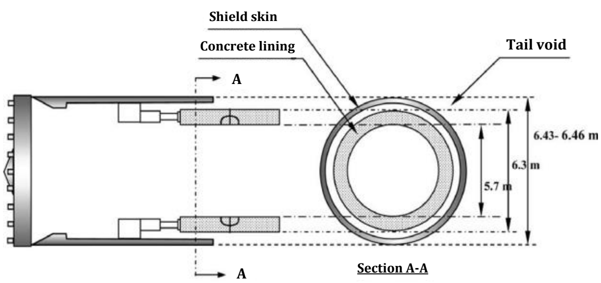


Figure 5. Schematic diagram showing a tail void between tunnel lining and liner [15].

4. Results and discussion

In this work, WEKA was utilized for developing an optimal RF-based predictor in order to forecast the maximum settlement. WEKA is an open source platform for machine learning implemented in Java [46]. The best values for the design parameters ($ntree$ and $mtry$) were determined through a trial and error process. As the number of trees in RF increases, the test set error rates converge to a limit, meaning that there is no over-fitting in large RFs [22]. The process starts using the suggested default values toward the minimum error in the OOB dataset. The default value for $ntree$ is 500 and the default value for $mtry$ can be determined via $[\log_2(\mathrm{N}) + 1]$, where N is the total number of variables [33].
The default $mtry$ value is $[\log_2(\mathrm{N}) + 1]$ (N is the total number of variables). We can suggest starting with default $mtry$ and then decreasing and increasing $mtry$ until the minimum error for the OOB dataset is obtained. As shown in figure 6 and table 2, the best results correspond to $ntree = 270$ and $mtry = 6$.

Table 2. Performance of RF models.

mtry	*ntree*	$\mathrm{ERR_{OOB}}$
2	270	7.6585
3	190	7.6909
4	380	7.8489
5	390	7.6739
6	270	7.5345
7	180	7.7567

The coefficient of correlation (CC), coefficient of determination (R^2), root mean square error (RMSE), and mean average error (MAE) are the statistical measures used to assess the performance of the proposed methodology. These statistical measures are defined as:

$$CC = \frac{\sum_{i=1}^{n}\left[\left(s_i - \bar{s}_i\right)\left(c_i - \bar{c}_i\right)\right]}{\sqrt{\sum_{i=1}^{n}\left(s_i - \bar{s}_i\right)^2\left(c_i - \bar{c}_i\right)^2}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(s_i - c_i\right)^2}{\sum_{i=1}^{n}\left(c_i - \bar{c}_i\right)^2} \tag{3}$$

$$RMSE = \left(\frac{\sum_{i=1}^{n}\left(s_i - c_i\right)^2}{n}\right)^{0.5} \tag{4}$$

$$MAE = \frac{\sum_{i=1}^{n}\left|s_i - c_i\right|}{n} \tag{4}$$

where, s_i and c_i denote the predicted and measured values, respectively; n is the number of measurements; $\bar{c}_i$ is the mean of c_i; and $\bar{s}_i$ is the mean of s_i.

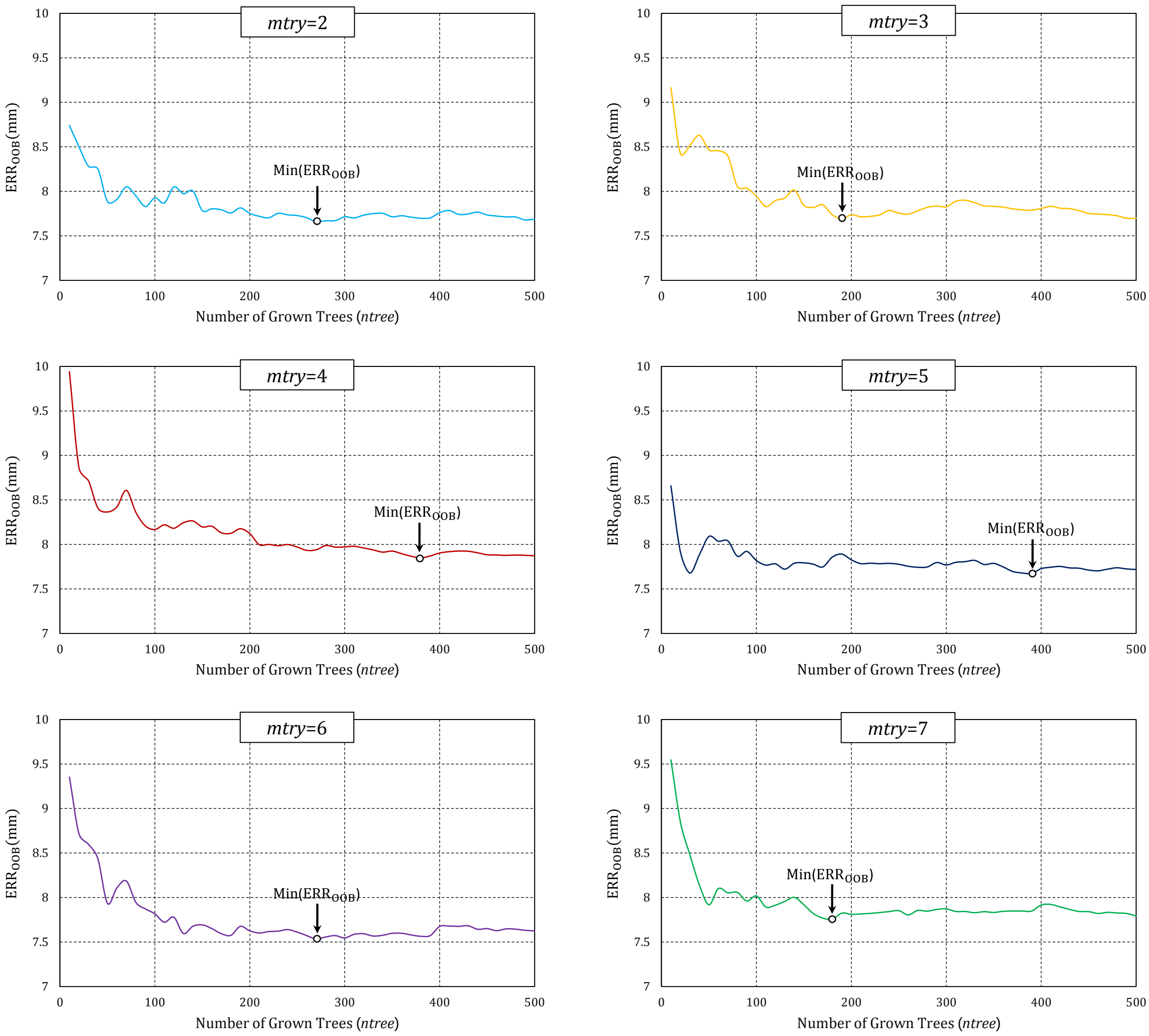


Figure 6. ERR_{OOB} vs. $ntree$ for different $mtry$ values. Arrow shows optimal number of grown tree that produced least out-of-bag estimate of error rate.

As shown in Fig. 7, the measured MSS and RF-based predicted values are very close to each other.

The RF accuracy was checked by comparing the results obtained with ANN, as a popular artificial intelligence (AI) algorithm [15], and Wavenet [19]. Wavenet is a hidden layer NN with a variable number of hidden nodes, which is based on the integration between the wavelet theory and ANN. Fig. 8 shows a comparison between the predicted ANN and Wavenet values. The statistical characteristics of the forecasted maximum settlements by the mentioned methods are compared in table 3. The results obtained indicate that the RF and Wavenet models perform better than the ANN model. It is worth noting that parameter tuning, data preprocessing, and feature selection are not required in RF. However, ANN requires some data pre-processing with de-correlation and normalization to increase the convergence speed of network [48].

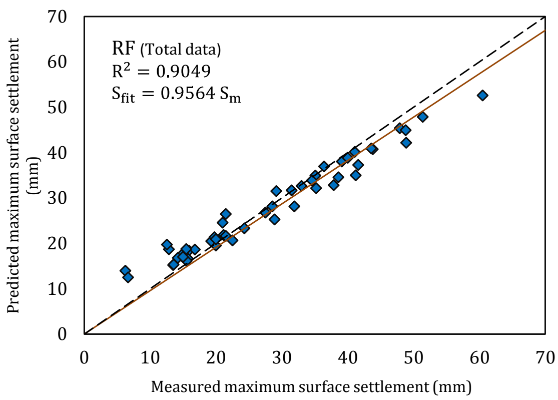


Figure 7. Measured vs. predicted MMS for RF model.

Table 3. Results of statistical evaluation.

Approach	CC	R^2	RMSE (mm)	MAE (mm)
RF	0.9838	0.9049	3.4270	2.6872
ANN [15]	0.9158	0.8373	5.0515	3.4299
Wavenet [19]	0.9670	0.9190	3.4550	1.8208

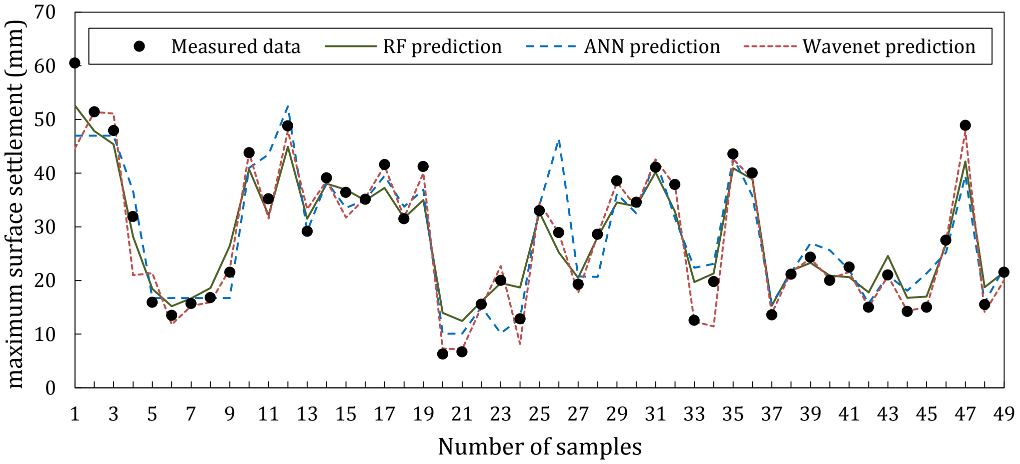


Figure 8. Comparison between measured values for MMS and predicted values using RF and ANN model for all datasets.

Moreover, RF has some other attracting advantages. For example, it is robust against over-fitting; it is very user-friendly, so that there are only two parameters needed to be considered; and RF is usually not very sensitive to their values; it can offer the data internal structure measure, which suggests that there is no need for an extra feature selection procedure.

The internal OOB error rate of RF could be used for classification accuracy assessment when there are limited samples for independent accuracy assessments; it is immune to irrelevant variables and outliers; it is not sensitive to the differences between data units and magnitudes, which suggests that it is not necessary to conduct data pre-processing such as normalizing or centering; and it can cope with badly unbalanced data; and [34].

Despite the RF advantages, it is mostly case-dependent and precise in the range of training data. However, it can be easily updated to yield better results, as new data becomes available.

5. Conclusion

Estimating the surface settlement caused by tunnel excavation is an important task. However, determining the maximum surface settlement (MSS) is challenging due to the number of parameters involved. In this work, the RF model is utilized to predict MSS in the EPB shield tunneling. RF is a pattern recognition method based on the "ensemble learning" strategy, which generates many predictors and averages their results to form a final prediction. RF, as a statistical learning modeling framework, does not require assumptions of normality of model variables, and can deal with non-linear relationships. Compared with ANN, which is the most popular artificial intelligence-based method, RF is easy for implementation with a higher accuracy. The results obtained from this study show that the best method among the three data mining methods for prediction of surface settlement is the RF method with a RMSE value of 3.4270. The RMSE values were found to be 5.0515 and 3.4550 for the ANN and Wavenet models, respectively. These three methods demonstrated promising results, and predicted the surface settlements of tunnels successfully. RF requires a less number of parameter for estimating MMS. Possibility of obtaining the generalization error estimate without splitting the dataset into learning and validation subsets make the RF designing process much faster than ANN.

References

[1] Atkinson, J. H. & Potts, D. M. (1977). Subsidence above shallow tunnels in soft ground. In Journal of the geotechnical engineering division, pp. 307-325.

[2] Attewell, P. B., Yeates, J. & Selby, A. R. (1986). Soil movements induced by tunnelling and their effects on pipelines and structures. Blackie Academic & Professional Blackie.

[3] Mair, R. (1983). Geotechnical aspects of soft ground tunnelling. In: International Symposium on Construction Problems in Soft Soils. Nanyang Technological Institute.

[4] O'reilly, M. & New, B. (1982). Settlements above tunnels in the United Kingdom-their magnitude and prediction. Brighton: Institution of Mining and Metallurgy.

[5] Peck, R. B. (1969). Deep excavations and tunnelling in soft ground. In Proceedings of the 7th International Conference on Soil Mechanics and Foundation Engineering. Sociedad Mexicana de Mecanica.

[6] Bobet, A. (2001). Analytical solutions for shallow tunnels in saturated ground. Journal of Engineering Mechanics, vol. 127, no. 12, pp. 1258-1266.

[7] Chou, W. I. & Bobet, A. (2002). Predictions of ground deformations in shallow tunnels in clay. Tunnelling and Underground Space Technology, vol. 17, no. 1, pp. 3-19.

[8] Loganathan, N. & Poulos, H. (1998). Analytical prediction for tunneling-induced ground movements in clays. Journal of Geotechnical and Geoenvironmental Engineering, vol. 124, no. 9, pp. 846-856.

[9] Park, K. (2004). Elastic solution for tunneling-induced ground movements in clays. International Journal of Geomechanics, vol. 4, no. 4, pp. 310-318.

[10] Sagaseta, C. (1987). Analysis of undraind soil deformation due to ground loss. Geotechnique, vol. 37, no. 3, pp. 301-320.

[11] Verruijt, A. & Booker, J. (1996). Surface settlements due to deformation of a tunnel in an elastic half plane. Geotechnique, vol. 46, no. 4, pp. 753-756.

[12] Ercelebi, S., Copur, H. & Ocak, I. (2011). Surface settlement predictions for Istanbul Metro tunnels excavated by EPB-TBM. Environmental Earth Sciences, vol. 62, no. 2, pp. 357-365.

[13] Melis, M., Medina, L. & Rodríguez, J. M. (2002). Prediction and analysis of subsidence induced by shield tunnelling in the Madrid Metro extension. Canadian Geotechnical Journal, vol. 39, no. 6, pp. 1273-1287.

[14] Mroueh, H. & Shahrour, I. (2002). Three-dimensional finite element analysis of the interaction between tunneling and pile foundations. International Journal for Numerical and Analytical Methods in Geomechanics, vol. 26, no. 3, pp. 217-230.

[15] Suwansawat, S. & Einstein, H. H. (2006). Artificial neural networks for predicting the maximum surface settlement caused by EPB shield tunneling. Tunnelling and Underground Space Technology, vol. 21, no. 2, pp. 133-150.

[16] Kohestani, V. R. & Hassanlourad, M. (2015). Modeling the Mechanical Behavior of Carbonate Sands Using Artificial Neural Networks and Support Vector Machines. International Journal of Geomechanics, vol. 16, no. 1, pp. 04015038.

[17] Santos, O. J. & Celestino, T. B. (2008). Artificial neural networks analysis of Sao Paulo subway tunnel settlement data. Tunnelling and underground space technology, vol. 23, no. 5, pp. 481-491.

[18] Xu, J. & Xu, Y. (2011). Grey correlation-hierarchical analysis for metro-caused settlement. Environmental Earth Sciences, vol. 64, no. 5, pp. 1249-1256.

[19] Pourtaghi, A. & Lotfollahi-Yaghin, M. (2012). Wavenet ability assessment in comparison to ANN for predicting the maximum surface settlement caused by tunneling. Tunnelling and Underground Space Technology, vol. 28, pp. 257-271.

[20] Ocak, I. & Seker, S. E. (2013). Calculation of surface settlements caused by EPBM tunneling using artificial neural network, SVM, and Gaussian processes. Environmental Earth Sciences, vol. 70, no. 3, pp. 1263-1276.

[21] Wang, F., Gou, B. & Qin, Y. (2013). Modeling tunneling-induced ground surface settlement development using a wavelet smooth relevance vector machine. Computers and Geotechnics, vol. 54, pp. 125-132.

[22] Breiman, L. (2001). Random forests. Machine learning, vol. 45, no. 1, pp. 5-32.

[23] Ardakani, A. & Kohestani, V. R. (2015). Evaluation of liquefaction potential based on CPT results using C4. 5 decision tree. Journal of AI and Data Mining, vol. 3, no. 1, pp. 82-89.

[24] Koohestani, V., Hassanlourad, M. & Bazargan-Lari, M. R. (2016). Prediction the Ultimate Bearing Capacity of Shallow Foundations on the Cohesionless Soils Using M5P Model Tree, Journal of Civil Engineering, vol. 27, no. 2, pp. 99-110. (in Persian).

[25] Dietterich, T. G. (2000). An experimental comparison of three methods for constructing ensembles of decision trees: Bagging, boosting, and randomization. Machine learning, vol. 40, no. 2, pp. 139-157.

[26] Ho, T. K. (1998). The random subspace method for constructing decision forests. Pattern Analysis and Machine Intelligence, IEEE Transactions on, vol. 20, no. 8, pp. 832-844.

[27] Ham, J., et al. (2005). Investigation of the random forest framework for classification of hyperspectral data. Geoscience and Remote Sensing, IEEE Transactions on, vol. 43, no. 3, pp. 492-501.

[28] Hernandez, P., et al. (2008). Predicting species distributions in poorly-studied landscapes. Biodiversity and Conservation, vol. 17, no. 6, pp. 1353-1366.

[29] Han, P., et al. (2009). Large-scale prediction of long disordered regions in proteins using random forests. BMC bioinformatics, vol. 10, no. 1, pp. 8.

[30] Watts, J. D., et al. (2009). Monitoring of cropland practices for carbon sequestration purposes in north central Montana by Landsat remote sensing. Remote Sensing of Environment, vol. 113, no. 9, pp. 1843-1852.

[31] Liu, M., et al. (2013). Comparison of random forest, support vector machine and back propagation neural network for electronic tongue data classification: Application to the recognition of orange beverage and Chinese vinegar. Sensors and Actuators B: Chemical, vol. 177, pp. 970-980.

[32] Tooke, T. R., Coops, N. C. & Webster, J. (2014). Predicting building ages from LiDAR data with

random forests for building energy modeling. Energy and Buildings, vol. 68, pp. 603-610.

[33] Kohestani, V. R., Hassanlourad, M. & Ardakani, A. (2015). Evaluation of liquefaction potential based on CPT data using random forest. Natural Hazards, vol. 79, no. 2, pp. 1-11.

[34] Liaw, A. & Wiener, M. (2002). Classification and Regression by randomForest. R news, vol. 2, no. 3, pp. 18-22.

[35] Suwansawat, S. (2002). Earth pressure balance (EPB) shield tunneling in Bangkok: ground response and prediction of surface settlements using artificial neural networks. Massachusetts Institute of Technology.

[36] Finno, R. J. & Clough, G.W. (1985). Evaluation of soil response to EPB shield tunneling. Journal of Geotechnical Engineering, vol. 111, no. 2, pp. 155-173.

[37] Clough, G. W. & Leca, E. (1993). EPB shield tunneling in mixed face conditions. Journal of geotechnical engineering, vol. 119, no. 10, pp. 1640-1656.

[38] Matsushita, Y., et al. (1995). Behavior of subway tunnel driven by large slurry shield. in Proceedings of International Conference on Underground Construction in Soft Ground. Balkema, Rotterdam.

[39] Chua, C. & Goh, A. T. (2005). Estimating wall deflections in deep excavations using Bayesian neural networks. Tunnelling and underground space technology, vol. 20, no. 4, pp. 400-409.

[40] Kung, G. T., et al. (2007). A neural network approach to estimating deflection of diaphragm walls caused by excavation in clays. Computers and Geotechnics, vol. 34, no. 5, pp. 385-396.

[41] Kim, C., et al. (2001). Neural network based prediction of ground surface settlements due to tunnelling. Computers and Geotechnics, vol. 28, no. 6, pp. 517-547.

[42] Chiorboli, M. A. & Marcheselli, P. P. (1996). Analysis and control of subsidence due to earth pressure shield tunneling in Passante Ferroviario of Milano. In Proceedings of International Conference on North American Tunneling96. Balkema, Rotterdam.

[43] Ocak, I. (2013). Interaction of longitudinal surface settlements for twin tunnels in shallow and soft soils: the case of Istanbul Metro. Environmental Earth Sciences, vol. 69, no. 5, pp. 1673-1683.

[44] Ocak, I. (2009). Environmental effects of tunnel excavation in soft and shallow ground with EPBM: the case of Istanbul. Environmental Earth Sciences, vol. 59, no. 2, pp. 347-352.

[45] Leca, E. (1989). Analysis of NATM and shield tunneling in soft ground. Virginia Polytechnic Institute and State University.

[46] Witten, I. H. & Frank, E. (2005). Data Mining: Practical machine learning tools and techniques. Morgan Kaufmann.

[47] Hung, C. J., et al. (2009). Technical Manual for Design and Construction of Road Tunnels-Civil Elements. US Department of Transportation, Federal Highway Administration, National Highway Institute, New York.

[48] Asghari, M. & Nematzadeh, H. (2016). Predicting air pollution in Tehran: Genetic algorithm and back propagation neural network. Journal of AI and Data Mining, vol. 4, no. 1, pp. 49-54.

نشریه هوش مصنوعی و داده کاوی

برآورد حداکثر نشست سطحی ناشی از حفر تونل با سپر فشار تعادلی زمین با استفاده از جنگل تصادفی

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چکیده:

تونل‌های زیرزمینی برای توسعه خطوط ریلی زیرزمینی به عنوان یک روش سریع، پاک و مؤثر برای انتقال مسافران در کلان‌شهرها، موردتوجه بسیاری قرار گرفته است. با توجه به اینکه این‌گونه تونل‌ها عموماً در مناطق شهری و در زیر سازه‌های مهم حفاری می‌شوند، تخمین نشست سطحی ناشی از حفر تونل ضروری است. در طی دهه‌های اخیر تلاش‌های بسیاری برای بررسی تأثیر فاکتورهای مؤثر در میزان نشست سطحی انجام شده است. در این تحقیق، مدل جنگل تصادفی (RF) برای پیش‌بینی حداکثر نشست سطحی (MMS) ناشی از حفر تونل با استفاده از سپر فشار تعادلی زمین (EPB) معرفی و بررسی شده است. نتایج حاصل نشان می‌دهد که RF یک روش قابل‌اعتماد برای تخمین MMS با استفاده از پارامترهای هندسی، زمین‌شناسی و عملیاتی ماشین است. با مقایسه نتایج حاصل با شبکه عصبی مصنوعی (ANN) به عنوان یک الگوریتم هوش مصنوعی محبوب، قابلیت کاربرد و دقت مدل RF به عنوان یک روش نوین، بررسی شده است. مدل RF پیشنهاد شده عملکرد بهتری نسبت به ANN نشان می‌دهد.

کلمات کلیدی: تونل، فشار تعادلی زمین (EPB)، حداکثر نشست سطحی (MMS)، جنگل تصادفی (RF).