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 (Bootstrap aggregating) [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 hyperspectral 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 \( (S_{\text{max}})_1, (S_{\text{max}})_2, \) and \( (S_{\text{max}})_i \) 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, \( S_{\text{max}} \), 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 (\( ERR_{\text{OOB}} \)), 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 \( i \)th element \( (y_i) \) of the training data set \( X \), all the trees are considered, in which the \( i \)th 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 \( g_{\text{OOB}} \) is developed. The OOB estimate of the error rate is computed as:

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

(1)

\( ERR_{\text{OOB}} \) 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 \( ERR_{\text{OOB}} \). Therefore, we first chose the optimal values for \( ntree \) and \( mtry \) that minimize \( ERR_{\text{OOB}} \), and then proceeded to develop the RF model. As \( ERR_{\text{OOB}} \) 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.

![Figure 1](image1)

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

Figure 2. Overview of EPB [47].
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

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

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameters</th>
<th>Count</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>StdDevα</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tunnel geometry</td>
<td>Tunnel depth (m)</td>
<td>17.89</td>
<td>24.82</td>
<td>22.05</td>
<td>1.93</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Distance from shaft (m)</td>
<td>33.60</td>
<td>3055.20</td>
<td>1320.27</td>
<td>969.50</td>
<td></td>
</tr>
<tr>
<td>Geological conditions</td>
<td>Geology at crown a</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Soft clay</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stiff clay</td>
<td>48</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>At invert</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Stiff clay</td>
<td>29</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Sand</td>
<td>20</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Invert to WT (m)</td>
<td>-5.97</td>
<td>0.96</td>
<td>3.20</td>
<td>1.93</td>
<td></td>
</tr>
<tr>
<td>EPBM operation factors</td>
<td>Face pressure (kPa)</td>
<td>14.50</td>
<td>131.00</td>
<td>54.73</td>
<td>28.62</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Penetrate rate (mm/min)</td>
<td>20.10</td>
<td>76.85</td>
<td>42.63</td>
<td>12.87</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Pitching angle (°)</td>
<td>-1.38</td>
<td>4.3</td>
<td>0.05</td>
<td>0.83</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tail void grouting pressure (kPa)</td>
<td>230.00</td>
<td>740.00</td>
<td>278.14</td>
<td>91.56</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Percent of tail void grout filling (%)</td>
<td>70.00</td>
<td>224.00</td>
<td>125.96</td>
<td>27.29</td>
<td></td>
</tr>
</tbody>
</table>

α Soil types at tunnel crown and invert are binary data.

β StdDev refers to the standard deviation.
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]. Tunnelling 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.

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 \[\log_2(N) + 1\], where N is the total number of variables [33]. The default mtry value is \[\log_2(N) + 1\] (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>
<thead>
<tr>
<th>mtry</th>
<th>ntree</th>
<th>ERR_{oob}</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>270</td>
<td>7.6585</td>
</tr>
<tr>
<td>3</td>
<td>190</td>
<td>7.6909</td>
</tr>
<tr>
<td>4</td>
<td>380</td>
<td>7.8489</td>
</tr>
<tr>
<td>5</td>
<td>390</td>
<td>7.6739</td>
</tr>
<tr>
<td>6</td>
<td>270</td>
<td>7.5345</td>
</tr>
<tr>
<td>7</td>
<td>180</td>
<td>7.7567</td>
</tr>
</tbody>
</table>

The coefficient of correlation (CC), coefficient of determination (R²), 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:

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

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (s_i - c_i)^2}{\sum_{i=1}^{n} (c_i - \bar{c})^2}
\]

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

\[
MAE = \frac{\sum_{i=1}^{n} |s_i - c_i|}{n}
\]

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 \(\bar{s}\) 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 MSS for RF model.

<table>
<thead>
<tr>
<th>Approach</th>
<th>CC</th>
<th>R^2</th>
<th>RMSE (mm)</th>
<th>MAE (mm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RF</td>
<td>0.9838</td>
<td>0.9049</td>
<td>3.4270</td>
<td>2.6872</td>
</tr>
<tr>
<td>ANN [15]</td>
<td>0.9158</td>
<td>0.8373</td>
<td>5.0515</td>
<td>3.4299</td>
</tr>
<tr>
<td>Wavenet [19]</td>
<td>0.9670</td>
<td>0.9190</td>
<td>3.4550</td>
<td>1.8208</td>
</tr>
</tbody>
</table>
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 MSS. 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


چکیده:
توئین‌های زیرزمینی برای توسعه خطوط ریلی زیرزمینی به عنوان یک روش سریع، پاک و مؤثر برای انتقال سافران در خلخ شهرها، مورد توجه و بررسی قرار گرفته است. با توجه به اینکه این گونه تونل‌ها عموماً در مناطق شری و در زیر سازه‌های زمین‌های مرم شده، نخستین نشست سطحی ناشی از حفر تونل ضروری است. در طی دهه‌های اخیر، هنگل‌های RF برای بررسی تأثیر فاکتورهای مأمور در میزان نشست سطحی انجام شده است. در این تحقیق، مدل جنگل تصادفی (RF) برای پیش‌بینی نشست سطحی (MMS) ناشی از حفر تونل با استفاده از سیر فشار تعادلی زمین (EPB) معرفی و بررسی شده است. نتایج حاصل نشان می‌دهد که RF یک روش قابل اعتماد برای تخمین MMS با استفاده از پارامترهای هندسی، زمین‌شناسی و عملیاتی مانند اینکه RF به عنوان یک الگوریتم مصنوعی محسوب می‌شود، قابلیت کاربرد و دقت مدل RF به عنوان یک روش مناسب برای تخمین MMS دارد. نتایج حاصل نشان می‌دهد که RF به عنوان یک روش مناسب برای تخمین MMS قابلیت کاربرد و دقت مدل RF به عنوان یک الگوریتم محسوب می‌شود.

کلمات کلیدی: توئین، فشار تعادلی زمین (EPB)، حفر تونل، RF، نشست سطحی (MMS)