Integrated Real-time Data-driven Model Framework for Optimization of Slurry Control Parameters in SPB-TBM Tunnelling

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Abstract. Maintaining the stability of excavation face is one of the most concerned problems in Slurry pressure balanced tunnel boring machine (SPB-TBM) construction. To overcome the uncertainty and errors caused by manual adjustment, this paper proposes a novel data-driven model framework to achieve the balance between slurry and soil pressure, which consists of two significant components: (1) an ensemble-learning-based model for predicting slurry pressure; (2) an optimization model based on greedy search strategy for slurry control parameter. The proposed framework was implemented and verified in Pearl River Delta Water Resources Allocation Project and the results demonstrated that the presented framework can make highly-accurate predictions for the slurry pressure and effectively adjust the control parameter values to achieve the balance between slurry and soil pressure.

1. Introduction

The construction of underground engineering plays a critical role in the sustainable development of European cities, by mitigating land use pressure and reducing environmental pollution. Tunnel boring machine (TBM), which is characterized by its high excavation efficiency, minimal environmental impact, and strong adaptability to the stratum, has become a popular option for various types of tunnel projects in Europe (Li et al., 2023), e.g. the London JLE metro (UK), Brescia metro (Italy) and Lyon metro (France) (Rallu et al., 2023). Particularly, slurry pressure balanced (SPB) TBM is widely used in the construction of submarine tunnel because of its advantages in maintaining the stability of excavation face (Zhang et al., 2021).

In SPB-TBM tunnelling, the balance between the slurry pressure ($P_s$) and the expected water-earth pressure ($P_e$) is crucial for both efficiency and safety. To reduce ground deformation by using air buffer to mitigate pressure fluctuations in the slurry chamber, indirect-type (German style with air chamber) SPB TBMs are currently mainly used. However, slurry control parameters are still manually adjusted based on the engineer's experience in practise, which has the characteristics of delay and unreliability. Recently, because of its advantages in modelling and controlling non-linear systems (Gao et al., 2019), machine learning (ML) methods have been proverbially employed in TBM tunnelling (Gao et al., 2021). Specifically, several researchers have explored the development of an ML-based approach for dynamically balancing $P_s$ and $P_e$ from various perspectives. Zhou et al. (2013) proposed a predictive control system for air chamber pressure using an Elman recurrent network (ENN). Liu et al. (2010) proposed a method combining mechanism analysis and least squares support vector machine (LS-SVM) technology for balancing chamber pressure. Liu and Zhang (2019) also used LS-SVM to predict earth pressure in the chamber during the tunnelling process. However, these studies do not fully consider the influence of the combined action of tunnelling operating and slurry control parameters, and pay more attention to the theoretical analysis and prediction tasks, without considering how to optimize the operating parameter strategy for practical application.
Ensuring high prediction accuracy is also a crucial challenge for ML tasks. Often, a single ML model performs not so well due to its high bias. However, combining multiple base learners to form an integration model may not always yield robust results due to the variance between the base models. To address this issue, ensemble learning algorithms have emerged as the state-of-the-art solution for improving the predictive performance of a single model by training multiple models and combining their predictions (Zhou and Zhou, 2021). Ensemble methods aims at combining several of these base learners to create a strong learner (or an ensemble model) to achieve better predictive performance. The use of ensemble learning-based methods has also been explored in the field of tunnelling construction for rock mass classification (Liu et al., 2020), estimation of advance rate (Zhou et al., 2021), etc. However, there is a dearth of research on optimizing operating parameters by predicting results using ensemble learning methods.

To obtain real-time and reliable parameter adjustments to balance the $P_s$ and expected water-earth pressure in SPB-TBM tunnelling, we proposed a novel data-driven model framework. The framework includes an ensemble learning-based model for predicting the $P_s$, and a greedy search-based optimization model for slurry control parameters. The continuation of this paper is organized as follows: Section 2 gives a detailed explanation of the methodology employed in this paper. Section 3 presents the application case and the framework execution results. Section 4 concludes the researches in this paper.

2. Methodology

The objective of the data-driven model framework proposed in this study is to predict the $P_s$ under different excavation and slurry parameters, and subsequently determine the optimal combination of slurry control parameters that minimizes the difference between the predicted $P_s$ and the expected $P_e$. According to the pressure balance control mechanism and the field engineering practise, the main parameters affecting the $P_s$ can be divided into two categories: (1) excavation parameters: the excavation speed ($v$), cutterhead rotation speed ($n$), cutterhead torque ($T$), penetration ($p$) and the total propulsion ($F$); (2) slurry control parameters: the air chamber pressure ($P_a$), slurry inlet flow ($Q_i$) and outlet flow ($Q_o$). The framework consists of two significant components, as depicted in Figure 1.

![Figure 1: Data-driven model framework](image-url)

The prediction model is designed to predict $P_s$ by establishing the complicated relationship between $P_s$ and the excavation and control parameters. The predictive performance of this model is critical and should be optimized to the best possible extent. The optimization model,
on the other hand, employs a greedy search technique to explore the parameter space and identify various value combinations of the control parameters. This technique is particularly suitable for scenarios where the variation range is small and the search step is limited. The optimization model then determines the optimal values of $Q_i$, $Q_o$ and $P_a$ by selecting the combination that results in the minimum difference between the predicted $P_s$ and the expected $P_e$.

### 2.1 Development of the prediction model

The construction process of the prediction model can be observed in Figure 2. Initially, the extracted samples are divided into training and test sets in a 9:1 ratio. Subsequently, the K-fold cross-validation technique is employed to determine the optimal combination of hyper-parameters. Finally, the models are fitted on the training set, their performance is evaluated on the test set, and the optimal model is selected. To test and compare the performance of different ML-based prediction models, three types of models are employed: (1) Base learners, including multi-linear regression (MLR), decision tree (DT) and back-propagation neural network (BPNN); (2) Bagging. We selected the random forest (RF) algorithm as the representative. (3) Boosting. AdaBoost, GBDT, XGBoost and LightGBM are utilized based on the optimal base learner.

![Figure 2: Construction process of prediction model](image)

The prediction performance measurements include mean squared error ($MSE$), mean absolute error ($MAE$), mean absolute percentage error ($MAPE$) and determination coefficient $R^2$, as Eq. (1) - Eq. (4).

\[
MSE = \frac{1}{n} \sum_{i=1}^{n} (y_i - \hat{y}_i)^2
\]  
(1)

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |y_i - \hat{y}_i|
\]  
(2)

\[
MAPE = 100\% \times \frac{1}{n} \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|
\]  
(3)

\[
R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}
\]  
(4)
Where $n$ is the number of samples, $y_i$ is the actual value for the $i$th sample, $\hat{y}_i$ is the corresponding predicted value and $\bar{y}$ is the mean value of the actual values.

### 2.2 Ensemble learning for regression

There are two frameworks to ensemble the base learners: the independent framework and the dependent framework (Sagi and Rokach, 2018). In the independent framework, each base learner is constructed independently of the others by manipulating the inputs, the outputs, the features, or by injecting randomness (Dietterich, 2002) (e.g., bagging.). In the dependent framework, each additional base learner will affect the weight distribution of all base learners (e.g., boosting).

**Bagging.** Introduced by Breiman in 1990s (Breiman, 1996), bootstrap aggregating (bagging for short) is commonly used to reduce the variance within a noisy dataset. In bagging algorithms, basic learners are trained independently, and the average of their prediction results is taken as the final result in the regression task, thus generating stability, as shown in Figure 3(a) (Sagi and Rokach, 2018).

One of the typical algorithms is random forest (RF) (Breiman, 2001), which is versatile enough to be applied to large-scale problems, and it performs excellently especially when the number of variables is much larger than the number of observations (Biau and Scornet, 2016). Based on a given training sample set $D_i = \{(X_1, Y_1), \ldots, (X_n, Y_n)\}$, an estimate $M_i$ of function $M$ is constructed. Assuming that there are $m$ bootstrap samples, then $m$ almost independent base learners $M_i(X)$ will be obtained, and the ensemble model for regression task is denoted by $M_{\text{reg}}(X) = \frac{1}{m} \sum_{i=1}^{m} M_i(X)$.

![Diagram of Bagging](image)

**Boosting.** In boosting, all the base learners are trained sequentially in a highly adaptive way as shown in Figure 3(b), in which each basic model depends on the previous models and tries to correct the predecessor (Schapire et al., 2012). Adaptive Boosting (AdaBoost) and Gradient boosting decision tree (GBDT) are two major algorithms in boosting.

![Diagram of Boosting](image)
AdaBoost is a machine learning meta-algorithm formulated in 1997 (Freund and Schapire, 1997). In each iteration, the weights of samples predicted incorrectly by the $k$th learner $H_k$ will be increased. All the base learners will be assigned a certain weight according to the strength of the prediction ability, and usually the base learners with small errors will be assigned a larger weight. The ensemble model is denoted by $H_{reg}(X) = \sum_{k=1}^{m} e_k H_k(X)$, where $e_k$ represents the weight of each weak estimation.

Instead of adjusting weights of samples, Gradient boosting decision tree (GBDT) focuses on the difference between the prediction and the ground truth, which tries to fit the new predictor to the residual errors $L_k$ made by the previous predictor rather than changing the weights for each incorrect and erroneous observation at each iteration (Yang et al., 2020). First, learn a model $F^l$ based on the training samples. Then in the following $k$ iterations, the base learner $F_k$ is trained according to $L_k = \sum_{i=1}^{N} (Y_i - F_k(X_i))^2$. The final prediction is calculated by $F_m(X) = F^1(X) + \rho \times \sum_{k=1}^{m} F_k(m)$, where $\rho$ controls the step size to combine all the weight regression estimations.

Under the framework of GBDT, extreme Gradient Boosting (XGBoost) (Chen et al., 2015) and Light Gradient Boosting Machine (LightGBM) (Ke et al., 2017) are two of the improved algorithms. XGBoost efficiently saves the hardware resources through system optimization and algorithmic enhancements. LightGBM utilizes Gradient-based One side Sampling (GOSS) and Exclusive Feature Building (EFB) techniques to make the model more capable to deal with large amounts of data.

### 2.3 Optimization of slurry pressure by greedy search strategy

To search for the optimal value combination of the slurry control parameters, the search space needs to be established in advance. The three-dimensional space is composed of $P_s$, $Q_i$, and $Q_o$. In search of $[P_{a, \text{min}}, P_{a, \text{max}}]$, $[Q_{i, \text{min}}, Q_{i, \text{max}}]$, $[Q_{o, \text{min}}, Q_{o, \text{max}}]$, $\{(P_a, Q_i, Q_o)\}$ (the search collection) is obtained. The objective function and the constraint conditions of slurry pressure optimization are shown in Eq. (5).

$$
\arg \min g = \arg \min |P_s - P_o|
$$

\[
\begin{align*}
\text{s.t.} \ & 
\begin{cases}
  P_a \in [P_{a, \text{min}}, P_{a, \text{max}}] \\
  Q_i \in [Q_{i, \text{min}}, Q_{i, \text{max}}] \\
  Q_o \in [Q_{o, \text{min}}, Q_{o, \text{max}}] \\
  Q_i < Q_o \\
  P_s = f(F, T, n, v, P_a, Q_i, Q_o)
\end{cases}
\end{align*}
\]

(5)

Where $f$ is the prediction model.

The greedy search algorithm is efficient to optimize the value combination of control parameters within their specified scopes. Basically, greedy search always makes the optimal choice by exploring in the whole search space. It will look at each step to ensure that the objective function is optimized globally. The process of the greedy search algorithm applied in the optimization of $P_i$ is as shown in Figure 4. The search ranges of the control parameters $P_a$ (Bar), $Q_i$ (m$^3$/h), and $Q_o$ (m$^3$/h) are [4, 4.5], [1980, 2000], [1980, 2000], respectively. The search step length $l_a$, $l_i$, and $l_o$ are 0.01 Bar, 0.1 m$^3$/h, 0.1 m$^3$/h, respectively.

| Input: $F$; $T$; $n$; $p$; $v$; $P_a$; $l$: search length of $P_a$; $l$: search length of $Q_i$; $l_o$: search length of $Q_o$. |  |  |
Figure 4: Pseudocode of greedy search algorithm

### 3. Case study

#### 3.1 Project overview and data preprocessing

The Pearl River Delta Water Resources Allocation Project passes through the core urban agglomeration of the Pearl River Delta. The SPB-TBM tunnelling section is around 84.9km long. The data used in our work were collected from the interval GS05# – GS06# with length about 3.39km. All the equipment parameters are collected automatically during the excavation process by the Programmable Logic Controller (PLC) system at an acquisition frequency of 1Hz. Obtained by the interfaces, the parameters of rings between 42 and 1313 from October 20th, 2020 are collected.

Three steps are executed sequentially in the data engineering process. To obtain more effective training data, the parameter values with the null value and the outliers detected according to the 3σ criterion are removed from the final dataset, and then we averaged the data on a minute-granularity basis. Eventually, total 82469 feature vectors were obtained for training and testing of the models. By random search (Bergstra and Bengio, 2012) with 6-fold cross validation, the optimal configuration of hyperparameters are shown Table 1.

<table>
<thead>
<tr>
<th>Algorithms</th>
<th>Hyper-parameters</th>
<th>Optimal Values</th>
<th>Algorithms</th>
<th>Hyper-parameters</th>
<th>Optimal Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>DT</td>
<td>Max_depth</td>
<td>30</td>
<td>RF</td>
<td>n_estimators</td>
<td>500</td>
</tr>
<tr>
<td>BPNN</td>
<td>Init_mode</td>
<td>&quot;uniform&quot;</td>
<td></td>
<td>max_depth</td>
<td>35</td>
</tr>
</tbody>
</table>
### 3.2 Results and discussion

In this study, a comparison experiment is conducted on the pre-processed dataset to predict $P_s$ using different prediction models. The statistic results were listed in Table 2. Initially, basic learners, including MLR, DT and BPNN, were constructed and compared. DT was found to perform the best among the base learners, achieving an $R^2$ value of up to 0.98, as shown in Figure 5(a). Thus, DT was selected for bagging and boosting algorithms.

Subsequently, bagging and boosting algorithms were constructed, and the evaluation results indicated that the AdaBoost model performed better than other models on the test set. The MSE, MAE, MAPE and $R^2$ were 0.002 Bar$^2$, 0.005 Bar, 0.127 % and 0.996, respectively. As show in Figure 5(b), the predicted values were almost entirely fitted with the actual values. Therefore, in the next Section, the optimal fitted AdaBoost model was selected as the prediction algorithm in the data-driven framework.

![Fitting results on the test set: (a) DT and (b) Adaboost](image)

**Figure 5:** Fitting results on the test set: (a) DT and (b) Adaboost

<table>
<thead>
<tr>
<th>Model</th>
<th>MSE(Bar$^2$)</th>
<th>MAE(Bar)</th>
<th>MAPE(%)</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>MLR</td>
<td>0.279</td>
<td>0.338</td>
<td>8.412</td>
<td>0.341</td>
</tr>
<tr>
<td>DT</td>
<td>0.008</td>
<td>0.014</td>
<td>0.355</td>
<td>0.980</td>
</tr>
<tr>
<td>BPNN</td>
<td>0.014</td>
<td>0.046</td>
<td>1.158</td>
<td>0.968</td>
</tr>
<tr>
<td>RF</td>
<td>0.004</td>
<td>0.016</td>
<td>0.394</td>
<td>0.992</td>
</tr>
</tbody>
</table>

**Table 2:** The evaluation results of base learning algorithms on the test set.
<table>
<thead>
<tr>
<th></th>
<th>AdaBoost</th>
<th>GBDT</th>
<th>XGBoost</th>
<th>LightGBM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>0.002</td>
<td>0.008</td>
<td>0.004</td>
<td>0.009</td>
</tr>
<tr>
<td>Precision</td>
<td>0.005</td>
<td>0.013</td>
<td>0.021</td>
<td>0.048</td>
</tr>
<tr>
<td>Recall</td>
<td>0.127</td>
<td>0.312</td>
<td>0.526</td>
<td>1.220</td>
</tr>
<tr>
<td>F1 Score</td>
<td>0.996</td>
<td>0.982</td>
<td>0.990</td>
<td>0.978</td>
</tr>
</tbody>
</table>

Based on theoretical $P_e$ calculations and engineering experience, the anticipated value of $P_e$ in the full section sandstone and mudstone fraction zones is 4 Bar. To further evaluate the performance of the data-driven model framework, 50 samples belonging to 25 rings were randomly selected from the entire dataset. These samples were compared with the actual values, and the results are illustrated in Figure 6.

As shown in Fig. 6(a), the values of $P_s$ optimized by the framework fluctuated slightly near the expected value (4 Bar), with a mean absolute gap between the optimized and the expected values of only 0.074 Bar. In contrast, the actual values fluctuated violently with a mean error of approximately 0.318 Bar. This is likely due to the fact that, as shown in Figure 6(b) to 6(d), during the actual tunnelling process, operators only set the $P_a$ to balance $P_s$ with $P_e$. Consequently, since $Q_i$ and $Q_o$ were not controlled, and the floating difference of $P_a$ was 0.912 Bar, the actual values of $P_s$ fluctuated violently.

The contrast results indicated the data-driven model framework is capable of ensuring that $P_s$ is more consistent with $P_e$ and can provide operators with more rational and reliable assistance in adjusting control parameters. Furthermore, the results suggest that the proposed framework has the superior ability to track the conditions of $P_s$ when these critical control parameters have changed.

![Figure 6: Optimized results: (a) $P_s$, (b) $P_a$, (c) $Q_i$, and (d) $Q_o$.](image-url)
4. Conclusions

The stability of the excavation face is crucial for safety and efficiency in SPB-TBM tunnelling. To address the limitations of manual adjustment of slurry control parameters, this paper proposed a data-driven model framework to achieve the slurry and earth pressure balance. Ensemble learning algorithms were employed to forecast $P_s$ more accurately based on the collected excavation and control parameters. A greedy search strategy was utilized to determine the optimal combination of slurry control parameters that minimized the difference between the predicted $P_s$ and the expected $P_e$.

The proposed framework was empirically tested using data collected from the Pearl River Delta Water Resources Allocation Project in China. The results of the analysis indicated that AdaBoost ensemble model exhibited superior performance compared to other ensemble models. Specifically, the AdaBoost model achieved higher accuracy and fewer errors, as evidenced by the MSE, MAE, MAPE and $R^2$ of 0.002, 0.005, 0.127 and 0.996, respectively. Thus, the expected $P_e$ can be accurately tracked.

Subsequently, a greedy search algorithm was employed to optimize the slurry control parameters, aiming to minimize the disparity between the predicted $P_s$ and the expected $P_e$. The results of the optimization process indicated that the proposed data-driven model framework was effective, with a mean absolute gap of only 0.074 Bar between the optimized $P_s$ and the expected $P_e$. This aspect of the analysis underscores the potential value of the proposed framework in offering valuable insights and guidance to operators involved in the tunnelling process.

In future research, the generalization issue of the proposed framework can be further improved to address the challenges posed by diverse tunnelling scenarios, geological conditions, and other relevant factors. This can be achieved by refining and expanding the framework, as well as integrating advanced machine learning techniques and optimization algorithms.

Acknowledgements

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Reference


