Prediction of Maximum Surface Settlements of Bai–Hua Tunnel Section based on Machine Learning

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Abstract. Research on the settlement caused by subway tunnel construction has always been an essential issue in tunnel research. However, due to the complexity of soil characteristics and construction parameters, using empirical formulas or numerical simulations to predict the maximum ground settlement is challenging to balance ease of use and accuracy. In recent years, with the rapid development of machine learning theory and computer science technology, machine learning algorithms are increasingly being used to predict the settlement. Random forest (RF) and artificial neural network (ANN) are often used to predict settlement. However, applying the extreme gradient boosting algorithm (XGB) in predicting the settlement is rarely seen. This article compares these three machines learning algorithms, using tunnel geometric parameters, shield construction parameters, and geological parameters as input parameters to predict the maximum ground settlement caused during tunnel construction. Compared with linear regression, the result shows these three machine learning algorithms can achieve higher quality results, and the stability of the RF and the XGB model is better than the neural network model. The XGB method can obtain the best results.

1. Introduction

Urban subway tunnels are close to surrounding buildings and municipal pipelines, and ground transportation is generally operating during tunnel construction. If a large settlement occurs in the tunnel project, it will cause damage to nearby buildings and pipelines and may affect road traffic safety. Therefore, accurate settlement prediction and control are essential issues in the study of subway tunnels.

The empirical formula method [1-5] is easy to use and often used to predict the maximum ground subsidence caused by tunnel engineering. However, the variability of the parameters is large, and the prediction accuracy of the ground settlement based on the empirical method cannot be guaranteed. With improved computer performance, numerical simulation has become a popular method for studying ground subsidence caused by shield excavation. Compared with empirical formulas and theoretical solutions, numerical methods can consider various complex conditions, such as the distribution of soil layers, physical and mechanical properties of soils, and the interaction between tunnels and soil. Kasper et al. [6] established a three-dimensional finite element model for the shield tunnelling construction process. Cambridge model was used to describe the soil behaviour. They studied groundwater, the friction between the shield and the soil, jack thrust, lining, and shield tail grouting. Mnoeh et al. [7] studied the selection of relevant parameters in the numerical simulation of shield construction. The acquisition of parameters relies on a large number of soil mechanical tests. For complex constitutive models, the tests are even more complicated. Therefore, this method is
suitable for the advanced research of particular and vital sites, and it is not easy to carry out for large-scale applications.

In the past two decades, machine learning algorithms have developed rapidly. Due to their powerful fitting capabilities, they simultaneously consider the influence of multiple parameters and are gradually applied to predict the ground subsidence caused by shield excavation. Artificial Neural Network (ANN) and Random Forest (RF) are two of the most widely used algorithms in this research direction. Chen et al. [8] used three artificial neural network algorithms (BP, RBF, GRNN) to predict the maximum surface settlement caused by shield tunnelling. Santos [9] et al. conducted a sensitivity analysis of parameters based on an artificial neural network model. They obtained the influence of parameters such as depth of the tunnel, the height of groundwater level, and excavation speed. In addition, a large number of studies have combined artificial neural network algorithms with various optimization algorithms (such as genetic algorithm, particle swarm algorithm, etc.) [10-13] to improve the accuracy of artificial neural network models. Random Forest (RF) is an integrated machine algorithm that builds multiple parallel independent weak evaluators simultaneously and integrates the modelling results of multiple evaluators to obtain the final prediction result. The accuracy of this algorithm is higher than a single model [14]. The core of XGBoost itself is an integrated algorithm based on gradient boosting tree implementation [15]. By constructing weak evaluators one by one and gradually accumulating multiple weak evaluators after various iterations, the modelling results of multiple evaluators are integrated to obtain the final result. Artificial Neural Networks (ANN) and Random Forests (RF) are widely used in this research area, and the application of XGBoost in this research field is rarely seen in the literature.

2. Project Overview

This construction site is the section between Baijiayuan Road Station and Huawu Road Station of Hangzhou Metro Line 3. The tunnel length is 1179.9m, and the earth pressure balance shield method is used for construction. The diameter of the shield is 6.2m. Figure 1 is a typical geological profile of the tunnel. The buried depth of the tunnel ranges from 19 to 28 m. TH mainly distributed in the silty clay layer and argillaceous siltstone. From top to bottom, the overburden layers are miscellaneous fill, plain fill, silty clay, silty clay, gravel mixed clay, and argillaceous siltstone. The physical and mechanical parameters of each soil layer are listed in table 1. A series of ground settlement measurement points are arranged above the central axis of the right tunnel. This paper selects 101 monitoring point data and combines geometry, geology, and construction parameters to conduct machine learning predictive analysis.

![Figure 1. Longitudinal tunnel profile.](image-url)
3. Model Training and Result Analysis

3.1. Feature Engineering

The factors affecting surface settlement can be classify as geometric tunnel parameters, shield construction parameters, and geological parameters. The geometric parameters of the tunnel include the tunnel’s buried depth and diameter. This article only studies a single line, the diameter of the tunnel does not change, so the diameter is not used as an input parameter. The buried depth of the tunnel is the only geometric parameter. Grouting pressure, grouting volume, soil pressure, thrust speed, total thrust, torque, these six tunnelling parameters that directly impact stratum settlement, so they are also selected as input parameters. The geological parameters include the thickness of the soil layers, the relative position of the physical parameters of the rock and soil itself, and the shield tunnel. The commonly used method is to directly input the $c$ and $\phi$ of the soil layer [16]. This method only considers the parameters of a single layer of soil. Some scholars use the one-hot method to code different types of soil layers [17]. This method considers the influence of soil layer type but cannot consider soil parameters. Some studies comprehensively consider soil layer depth by defining correction factors, thickness, physical and mechanical properties, and get weighted $c$, $\phi$, $k_h$, $k_v$ as new input parameters [18]. This paper refers to the calculation method of Chen [18] to obtain new soil parameters as input parameters. All influencing factors considered in this paper are shown in figure 2. Based on the 101 ground subsidence measurement points selected in this paper, the sample data are processed according to the above method to obtain the parameters directly input to the model. The final input and output data of some samples are shown in table 2.
Figure 2. Relationship between surface settlement and influencing factors.

Table 2. Data samples.

| sample | depth (m) | grouting pressure (bar) | grouting filling (m3) | face pressure (bar) | thrust speed (cm/min) | thrust (MN) | torque (MN·m) | $c$ (kPa) | $\phi$ (°) | vert. permeability coefficient $k_v$ (cm/d) | horiz. permeability coefficient $k_h$ (cm/d) | maximum settlement (mm) |
|--------|-----------|-------------------------|-----------------------|---------------------|-----------------------|-------------|--------------|---------|---------|--------------------------------------------|--------------------------------------------|----------------------|
| 1      | 24.12     | 1.40                    | 4.76                  | 1.74                | 5.50                  | 9.26        | 2.14         | 9.57    | 17.88   | 14.49                                     | 15.71                                     | 12.62                |
| 2      | 24.23     | 1.40                    | 4.68                  | 1.46                | 5.50                  | 9.06        | 2.10         | 9.52    | 17.97   | 12.79                                     | 13.77                                     | 9.21                 |
| 3      | 24.50     | 1.40                    | 4.68                  | 1.64                | 5.50                  | 9.78        | 2.28         | 9.37    | 18.23   | 9.21                                      | 9.69                                      | 5.52                 |
| 4      | 25.78     | 1.40                    | 4.72                  | 1.68                | 5.50                  | 8.42        | 2.14         | 13.41   | 34.05   | 8.02                                      | 8.70                                      | 1.09                 |
| 5      | 25.86     | 1.40                    | 4.86                  | 1.64                | 5.40                  | 9.12        | 2.24         | 13.78   | 34.44   | 7.05                                      | 7.60                                      | 0.80                 |
| 6      | 25.96     | 1.40                    | 5.22                  | 1.50                | 5.00                  | 9.46        | 2.15         | 14.24   | 34.95   | 6.29                                      | 6.75                                      | 1.61                 |
| 7      | 26.03     | 1.40                    | 4.80                  | 1.62                | 4.90                  | 9.42        | 2.07         | 14.42   | 33.94   | 6.03                                      | 6.46                                      | 2.03                 |
| 8      | 26.37     | 1.40                    | 4.38                  | 1.44                | 5.10                  | 6.76        | 1.46         | 14.26   | 20.62   | 8.68                                      | 9.50                                      | 0.11                 |
| 9      | 26.43     | 1.36                    | 4.62                  | 1.50                | 5.20                  | 6.68        | 1.50         | 14.25   | 20.59   | 8.88                                      | 9.73                                      | 1.81                 |
| 10     | 26.74     | 1.40                    | 4.56                  | 1.52                | 5.60                  | 6.36        | 1.22         | 11.31   | 29.08   | 7.97                                      | 8.22                                      | 0.37                 |

3.2. Best Parameters

Use the scikit-learn library in Python to implement random forest, neural network algorithms and extreme gradient boosting algorithm. The number of decision trees can significantly affect the performance of the random forest. The number of decision trees calculated in this article is 1-100. One hidden layer can achieve nonlinearity prediction. Therefore, only the single-layer neural network performance is studied. The number of calculated neurons is 1 to 100, and there are 100 combinations in total. The activation function used is ReLU (rectified linear unit function). The number of weak evaluators in XGB ranges from 1 to 100. The performance index uses the root mean square error (RMSE). The smaller the value, the better the performance. The calculation formula is as follows:

$$ RMSE = \left( \frac{1}{N} \sum_{i=1}^{N} (y_i - d_i)^2 / N \right)^{1/2} $$

$N$ is the number of samples, $y_i$, and $d_i$ represent the settlement predicted by the machine learning algorithm and the actually measured settlement. For each model, a five-fold cross-validation method is used to calculate five times, and the average value is calculated as the final evaluation indicator. The relationship between the performance indicators and hyperparameters of the random forest, neural network, and extreme gradient boosting algorithm is plotted in figure 3. It can be seen from figure 3 that compared with the linear regression (RMSE equals 4.58), the performance of the random forest is poorer than the linear regression only when $n$ equals 1. At this time, the random forest degenerates into a decision tree model. When $n$ is small ($n<7$), as $n$ increases, the performance improves fast. When $n=6$, there is a local minimum point. Generally speaking, as the number of decision trees increases, the model's performance continues to improve. After $n$ equals 20, the performance improvement is not apparent. The optimal performance is reached when $n$ is 52. At this time, RMSE equals 3.31mm. For neural networks, slight changes in the number of neurons lead to large
fluctuations in the algorithm's performance, and sometimes the performance is bad than linear regression. When the number of neurons in the hidden layer of a single-layer neural network is 40, the optimal performance is achieved, and RMSE equals 3.53mm. For XGB, as the number of weak estimators increases, the model's performance continues to improve, and the performance improvement is not evident after n equals 30. When the number of evaluators is 75, optimal performance is achieved. At this time, RMSE equals 1.11mm. Overall, the performance of the XGB model is significantly better than other models.

Figure 3. Three methods performance vs n.

3.3 Result Analysis
Figures 4, 5, and 6 plot the comparison of train and test results of optimal random forest, neural network, and XGB models. Most of the data points in the figure are distributed near the line, indicating that the predicted values of the training data and test data are close to the measured values. The optimal model trained using the random forest model, neural network, and XGB model can all accurately predict the ground subsidence of this project. The settlement value has a large number of points in the interval of 0~5mm. Hence, it appears that the points in this interval are concentrated. The predicted value and the measured value have a significant deviation in the area of 5~15mm because only a few train samples in this area. Less training led to poor predict results. In general, the training and prediction results of XGB model are better than random forest and neural network models.

Figure 5. Predicted result of neural network model.

Figure 6. Predicted result of XGB model.
4. Conclusion
Based on three machine learning algorithms: random forest, neural network, and XGB, this paper predicts the maximum settlement of the tunnel surface in the Bai-Hua section. Eleven influencing factors were selected from geometric tunnel parameters, shield construction parameters, and geological parameters. And training and prediction sample data were constructed. RMSE was chosen as the evaluation index to establish the best random forest, neural network, and XGB model. The following conclusions can be drawn:

1) Compared with linear regression model, random forest, neural network, and XGB are more effective ways to predict the maximum surface settlement of shield tunnel construction. By adjusting the number of random forest decision trees, the number of neurons in the hidden layer of the neural network, and the number of weak evaluators in XGB, all three machine learning models can achieve high accuracy.

2) For the data in this paper, the performance and stability of the XGB model are better than random forest and neural networks.

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