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Original Paper

Intelligent Optimization Method of Shield Tunneling Parameters Based on Machine Learning

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Abstract

Aiming at the problems that the parameter setting in the process of shield tunneling depends on artificial experience and is difficult to adapt to complex and changeable geological conditions, this paper studies the intelligent optimization of shield tunneling parameters based on machine learning. Combined with the nonlinear and multi-factor coupling characteristics of shield construction, three machine learning algorithms, random forest (RF), support vector machine (SVM) and BP neural network, are selected to construct a parameter optimization model with geological parameters and tunneling parameters as input and tunneling speed as output. The mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) were selected as evaluation indexes to evaluate the performance of the model. The results show that all three models can predict the tunneling speed, but the performance difference is significant. Among them, the random forest model performs best in nonlinear mapping and anti-interference ability through ensemble learning and feature random selection. Its R^2 reaches 0.967, and the prediction accuracy is significantly better than that of BP neural network and support vector machine model. This study provides an effective method support for intelligent prediction and dynamic optimization of shield tunneling parameters, and has practical reference value for improving the intelligent level of shield construction.

Keywords

Machine Learning, Shield tunnel construction waste, Blasting parameters

1. Introduction

Under the background of accelerating the construction of infrastructure projects such as urban rail transit and underground comprehensive pipe gallery in China, the shield construction method has gradually developed into one of the leading technologies in the field of underground engineering construction due to its outstanding advantages such as fast construction speed and slight impact on the surrounding environment. The shield tunneling operation is a typical nonlinear dynamic process, which is characterized by the integration of multi-physical field coupling and multi-factor interaction (Hong Kairong, 2015). Reasonable determination of tunneling parameters not only directly affects the construction efficiency, engineering quality, construction safety and engineering cost, but also is the core link of shield construction process control. Therefore, it is urgent to establish a theoretical method and technical system that can quickly predict the tunneling parameters and effectively control the tunneling attitude (Shahrour & Zhang, 2021; Shi Maolin, Sun Wei, & Song Xueguan, 2021).

At present, the setting of shield tunneling parameters mainly depends on the experience of field engineers, and is usually adjusted manually in combination with geological survey data. This traditional method has obvious limitations: on the one hand, complex geological conditions make it difficult for experience-based parameters to adapt to the dynamic construction environment, which is easy to cause various problems, thus affecting the construction progress and safety; on the other hand, the response speed of the manual adjustment method is slow, and it is difficult to achieve real-time optimization of parameters. There are difficulties in taking into account the construction efficiency and engineering quality, especially under complex geological conditions. Therefore, it is urgent to develop a scientific, efficient and intelligent optimization method for shield tunneling parameters.

In recent years, machine learning has been gradually applied to the field of underground engineering due to its excellent nonlinear fitting and real-time prediction capabilities, and has made a series of progress in geological condition identification, construction risk early warning, and tunneling parameter prediction. For example, Cachimp et al. (2019) used BP neural network to predict the cutterhead torque based on the foam injection ratio. The measured results show that the model is helpful to optimize the TBM construction process. Based on the railway tunnel project, a prediction model between shield parameters and tunneling rate based on BP network is constructed (Zhu Xiaozao, 2020). Based on the project of Shanghai Metro Line 9, Sun et al. (2009) used BP neural network to quantitatively analyze the relationship between tunneling speed, earth pressure, unearthed quantity and total thrust, cutterhead torque, and realized effective prediction of the latter two. Li Chao et al. (2017) took the soil weight, internal friction angle, etc.as input parameters, and the propulsion speed, total thrust, etc.as output, and realized the prediction of total thrust, cutterhead torque and power. Compared with the traditional empirical method, the parameter optimization method based on machine learning can make full use of the large amount of data generated in the shield construction process, and construct the mapping relationship between parameters and tunneling efficiency, surface subsidence and other indicators through algorithm training, so as to realize the intelligent prediction and dynamic adjustment of tunneling parameters, effectively reduce the dependence on artificial experience, improve the accuracy and real-time performance of parameter optimization, and provide technical support for the intelligent control of shield construction.

At present, the machine learning research on the prediction of tunneling parameters mostly adopts a single algorithm. Therefore, this paper takes the intelligent optimization of shield tunneling parameters as the research goal, integrates a variety of machine learning algorithms, and systematically discusses its application process and implementation method in parameter optimization. By combing the relevant influencing factors, the optimization model is constructed to realize the intelligent optimization of key parameters, so as to solve the problems of unreasonable parameter setting and lagging response, improve the intelligent level, construction efficiency and engineering quality of construction, and provide theoretical basis and technical reference for practical engineering.

2. Research Methods

This paper focuses on the intelligent optimization of shield tunneling parameters. Combined with the core advantages of machine learning technology, a complete research method system of "data preprocessing, model construction, model training and verification, parameter optimization and application" is constructed. The specific research process is shown in Figure 1.

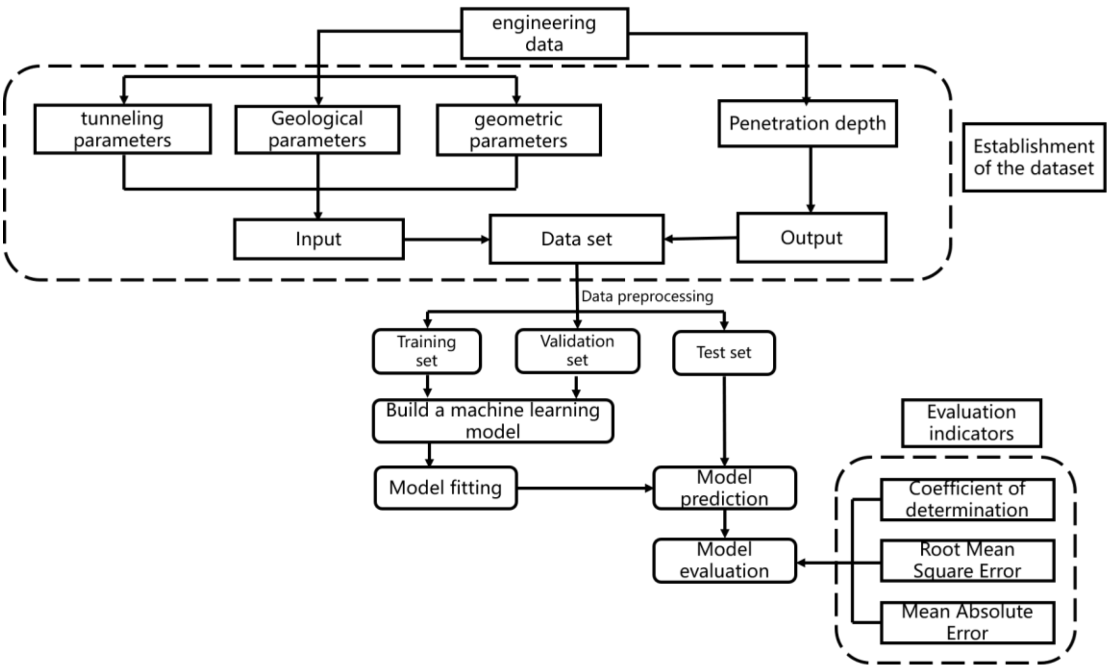


Figure 1. Process of Shield Tunneling Parameter Prediction Method Based on Machine Learning

In view of the nonlinear and multi-factor coupling characteristics of shield tunneling parameter optimization, this paper selects three commonly used machine learning algorithms: random forest, support vector machine and BP neural network to carry out penetration prediction research. Through the comprehensive comparison of the applicability of the three algorithms, the algorithm with strong generalization ability, fast convergence speed and good anti-interference is selected as the core model. On this basis, taking the screened geological parameters and construction basic parameters as input variables, and the optimal tunneling parameters as output variables, the optimization model of shield tunneling parameters based on machine learning is constructed.

2.1 Data Collection and Preprocessing

Based on the construction monitoring data in the actual shield project, this paper collects the tunneling parameters such as penetration, cutterhead speed, unearthed quantity, grouting pressure, thrust and related geological parameters. Aiming at the problems of missing, abnormal and redundancy in the data, the missing values are processed by means of mean filling and linear interpolation.

2.2 Machine Learning Model Selection and Construction

Aiming at the nonlinear and multi-factor coupling characteristics of shield tunneling parameter optimization, the applicability of three machine learning algorithms, BP neural network, random forest and support vector machine, is comprehensively compared, and the algorithm with good generalization ability is selected as the core model. Taking geological parameters and tunneling parameters such as penetration, cutterhead speed and thrust as input variables, and tunneling speed as output variables, an optimization model of shield tunneling parameters based on machine learning is constructed. The network structure and parameter configuration of the model, the dimensions of input and output, the loss function and the optimizer are determined, so as to complete the preliminary construction of the model.

2.3 Model Training and Validation

The preprocessed data set is divided into training set, validation set and test set according to the ratio of 8: 1: 1. The training set is used for model training and parameter optimization, and the test set is used to verify the performance of the model. The final model selects mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) as evaluation indicators, and evaluates based on test set data to analyze the prediction accuracy and optimization effect of the model.

3. Results and Analysis

In order to test the effectiveness and superiority of the three machine learning models of RF, SVM and BP neural network in the prediction of shield tunneling speed, this paper takes 626 sets of shield construction measured data as research samples, and divides them into training set, test set and verification set according to the ratio of 8: 1: 1, including 499 training sets, 63 test sets and 64 verification sets. The MAE, RMSE and coefficient of determination (R^2) were selected as the evaluation indexes of model prediction performance. The smaller the values of MAE and RMSE, the smaller the deviation between the predicted value and the actual value of the model. The closer R^2 is to 1, the better the fitting effect of the model and the higher the prediction accuracy.

3.1 Prediction Results

The test results of the predictive performance indicators of the three models are shown in Table 1.

Table 1. The Prediction Results of the Three Models

Machine learning model	MAE	RMSE	R^2
RF	0.032	0.048	0.967
SVM	0.075	0.102	0.883
bp neural network	0.098	0.135	0.821

3.2 Comparative Analysis of Model Prediction Performance

It can be seen from Table 1 that all three machine learning models can predict the tunneling speed of shield machine, but the difference in prediction performance is obvious. Among them, the RF model has the best prediction effect, the BP neural network model has the worst performance, and the performance of the SVM model is between the two.

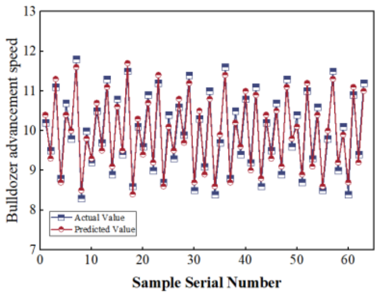
The RF model has the best performance, which is mainly attributed to the fact that the model uses multiple decision trees for integrated learning. Through Bootstrap sampling and feature random selection, it effectively alleviates the problem that a single decision tree is easy to over-fit, and has strong generalization ability. At the same time, the model has strong adaptability to the data characteristics such as multi-factor coupling and nonlinearity in the process of shield tunneling. It can better excavate the complex mapping relationship between the input parameters such as cutterhead speed, total thrust and torque and the tunneling speed, and has strong anti-interference ability to abnormal data. Therefore, the prediction error is the lowest and the fitting effect is the best. Its R^2 reaches 0.967, MAE and RMSE are as low as 0.032 m / min and 0.048 m / min, respectively, indicating that the model can accurately predict the tunneling speed of shield machine.

The BP neural network model has the most unsatisfactory prediction effect. The main reason is that the model, as a multi-layer feedforward neural network, has a strong dependence on data quality and is susceptible to the distribution of training samples. In the training process, problems such as gradient disappearance and over-fitting are prone to occur. In addition, the model does not fully fit the nonlinear coupling relationship of each parameter in the shield tunneling process, and it is difficult to effectively capture the complex correlation between the input parameters and the tunneling speed, resulting in a relatively large prediction error. The R^2 is only 0.821, and the MAE and RMSE are as high as 0.098 and 0.135, respectively. The prediction accuracy is difficult to meet the requirements of practical engineering applications.

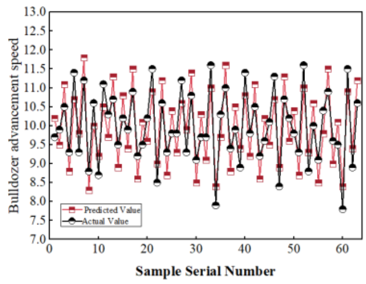
The prediction performance of the SVM model is between the two. The model realizes nonlinear fitting by mapping data to high-dimensional feature space, which has certain advantages in small sample data scenarios. However, it is sensitive to parameter settings such as kernel function and penalty coefficient, and has limited ability to deal with the complex correlation of large amounts of data in the process of shield tunneling. Therefore, its prediction accuracy is lower than that of random forest model, but better than that of BP neural network model. The R^2, MAE and RMSE of the model were 0.883,0.075 and

0.102, respectively.

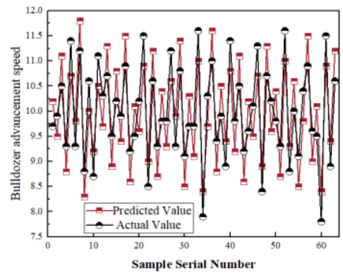
In order to further intuitively present the prediction effect of the three models, 63 data of the test set are selected as samples, and the actual and predicted values of the tunneling speed of the three models are extracted respectively, as shown in Figure 2.



RF model fitting results



SVM model fitting results



BP-neural network model fitting results

Figure 2. Fitting Results of Three Models

Based on the prediction performance index of the three machine learning models and the comparative analysis of the actual value and the predicted value, it can be seen that the RF model has the best effect in the prediction of the tunneling speed of the shield machine, with the highest prediction accuracy and the smallest error. It can accurately capture the complex nonlinear relationship between the input parameters and the tunneling speed, and can be used as the preferred model for the prediction of the tunneling speed of the shield machine. The prediction accuracy of BP neural network model is relatively low, which is difficult to meet the needs of practical engineering prediction. The SVM model can be used as an auxiliary prediction model. The research results provide a reliable method support for the intelligent prediction of shield tunneling speed, and also lay a good foundation for the intelligent optimization of subsequent shield tunneling parameters.

4. Conclusion

Based on the three machine learning algorithms of RF, SVM and BP neural network, this paper constructs a prediction model of shield tunneling speed, and systematically evaluates the performance of the model with the measured data. The main conclusions are as follows:

(1) All three machine learning models can predict the shield tunneling speed, but there are obvious differences in prediction performance. The RF model performed best in terms of prediction accuracy and fitting effect, with R^2 of 0.967, MAE and RMSE of 0.032 and 0.048, respectively. SVM model is the second, R^2 is 0.883; the prediction effect of BP neural network model is the worst, and R^2 is only 0.821.

(2) RF model can effectively excavate the nonlinear coupling relationship between multiple parameters

in the process of shield tunneling, and it is the optimal model to realize the accurate prediction of tunneling speed.

(3) This study verifies the feasibility and effectiveness of the machine learning method in the optimization of shield tunneling parameters. The constructed model can provide parameter setting basis for shield construction under complex geological conditions, reduce the dependence on artificial experience, and improve construction efficiency and safety. Subsequent research will further integrate more influencing factors and explore the interpretability and dynamic adaptive ability of the model, so as to promote the development of shield construction to a higher level of intelligence.

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