Modern Management Science & Engineering
ISSN ISSN 2052-2576
Vol. 8, No. 2, 2026
www.scholink.org/ojs/index.php/mmse

*Original Paper*

# Intelligent Prediction and Parameter Optimization Analysis of Shield Construction Attitude Based on Random Forest Model

Li Liu[1], Qianqian Cheng[1,*], Xiaotao Du[1], & Airu Sun[1]

[1] School of Civil Engineering, Qingdao City University, Qingdao, Shandong 266106, China.

[*] Corresponding Author

Received: February 19, 2026 Accepted: March 18, 2026 Online Published: April 27, 2026

doi:10.22158/mmse.v8n2p162 URL: http://dx.doi.org/10.22158/mmse.v8n2p162

***Abstract***

*Aiming at the problem that the attitude deviation is affected by multi-parameter coupling and the prediction accuracy is insufficient in the process of shield construction, this paper uses the random forest algorithm to construct the attitude deviation prediction model based on the field measured construction data. By sorting and optimizing the importance of input parameters, eliminating redundant features and optimizing the model structure, the accurate prediction of attitude deviation is realized. The results show that the goodness of fit ($R^2$) of the model after parameter optimization is 0.917, the error indexes are significantly reduced, and the predicted values are in good agreement with the real values. The total thrust, cutterhead torque and earth pressure are the key parameters affecting the attitude deviation. The research shows that the random forest model based on parameter optimization can effectively improve the accuracy of attitude prediction, which can provide technical reference for the intelligent control of shield construction alignment.*

***Keywords***

*machine learning, random forest, shield construction*

## 1. Introduction

Shield construction has become a key technical means for urban underground space development and tunnel engineering construction in China.Its construction quality and tunnel forming accuracy are highly dependent on the attitude control level of shield machine. The shield attitude deviation directly reflects the deviation degree between the tunneling direction and the design axis. Under complex geological conditions, improper matching of tunneling parameters, sudden change of stratum soft and hard, uneven thrust of oil cylinder and other factors will lead to the deviation of attitude from the design trajectory. If it fails to predict and adjust in time, it is easy to cause engineering problems such as tunnel overrun, segment damage and excessive surface deformation, which directly affects construction safety and engineering benefits. Therefore, it is of great practical significance to carry out high-precision prediction research on shield machine attitude deviation to realize active control of tunneling process and improve the intelligent level of construction.

Traditional shield attitude control mainly relies on field technicians to manually adjust according to experience, and passive correction is carried out through real-time monitoring data. This method is difficult to fully describe the complex nonlinear relationship between geological conditions, construction parameters and attitude changes. In the face of long-distance, large buried depth and high-risk tunnel projects, the problems of prediction lag and insufficient control accuracy are particularly prominent.

There are three main methods for predicting shield attitude deviation : mechanical analysis method, empirical fitting method and machine learning method. Among them, although the mechanical analysis method is based on the moment balance equation, it is difficult to capture the uncertainty characteristics of the formation load due to the simplification of the excavation process, and the prediction accuracy is limited (SHEN & YUAN, 2020). The empirical fitting method is subject to many idealized assumptions, which is out of touch with engineering practice and lacks application feasibility (KUWAHARA et al., 1988). In recent years, with the rapid development of data-driven technology in the field of geotechnical engineering, the use of machine learning methods to mine massive construction data has become an important direction for shield attitude analysis and prediction.

XIAO H et al. (2021) used the measured data of EPB shield machine to compare various algorithms and found that LSTM and GRU had the best accuracy in shield attitude prediction, and constructed a deviation warning system. Based on the analysis of attitude influence parameters, Ding et al. (2016) established a model based on kinematics theorem and used BP neural network to predict control parameters. Wu et al. (2021) took Shanghai Metro Line 14 as the background to reveal the interaction mechanism between stratum, tunneling parameters and shield attitude. Support vector machine was used to establish parameter optimization and attitude prediction model, and good prediction results were obtained. Hu et al. (2021) used support vector machine algorithm to establish a prediction model with tunneling parameters, geometric parameters and stratum characteristic parameters as input and shield vertical attitude as output. Although the prediction model is constructed by machine learning algorithm. But there is no optimization based on the input parameters.

In view of this, based on the measured data of the shield construction site, this paper selects the key parameters such as thrust, torque, speed, soil pressure, slurry parameters, shield tail clearance as input characteristics, and takes the horizontal attitude deviation and vertical attitude deviation of the shield machine as the prediction target. A prediction model of shield attitude deviation based on random forest is constructed. Then, parameter correlation analysis and feature importance evaluation are carried out to optimize the input parameters, eliminate redundant features and retain key influencing factors, so as to achieve efficient and accurate prediction of shield attitude deviation, so as to provide reliable methods and technical reference for intelligent control of shield tunneling attitude.

## 2. Research Methods

Among various machine learning algorithms, the random forest algorithm has significant advantages such as high model stability, strong anti-interference ability, good adaptability to high-dimensional features, and difficulty in overfitting. It can effectively deal with nonlinear prediction problems under multi-factor coupling, and is suitable for multivariate prediction of shield attitude deviation. At present, most of the research focuses on the attitude control algorithm or the analysis of a single influencing factor. Combined with the multi-source data measured in the field, the attitude prediction research for engineering practicability still needs to be improved.

In this paper, the attitude deviation of shield machine is taken as the prediction object, and the random forest algorithm is used to construct the prediction model. Firstly, the basic attitude deviation prediction is completed, and then the parameter sensitivity analysis and input parameter optimization are carried out by successively eliminating the input parameters. Finally, the optimal input parameter combination with lightweight and high precision is obtained. The research methods mainly include data preprocessing, basic prediction model construction, model performance evaluation, and input parameter optimization.

### *2.1 Data Collection and Preprocessing*

Taking the field measured shield construction data as the research sample, several construction parameters such as thrust, torque, cutterhead speed, earth pressure, slurry inlet and outlet parameters, shield tail clearance, and excavation quantity are selected as the original input characteristics, and the horizontal attitude deviation and vertical attitude deviation are taken as the output targets.

### *2.2 Construction of Basic Attitude Deviation Prediction Model Based on Random Forest*

The basic prediction model of shield attitude deviation based on random forest algorithm is constructed by taking all the primary input parameters after field screening as the input dimension of the model, and taking the horizontal attitude deviation and vertical attitude deviation of shield machine as the double target output variables. In the process of model training, random forest can independently learn the complex nonlinear correlation between multi-source construction parameters and attitude deviation through layer-by-layer feature splitting and node judgment. It does not need to presuppose empirical formulas or mechanical assumptions, and can fully explore the influence mechanism of attitude change under the coupling of parameters such as total thrust, cutterhead torque, earth pressure, shield tail clearance and propulsion speed. After the model is trained, the attitude deviation inference prediction can be performed on the test set samples, and the output results of multiple decision trees are averaged to obtain the final horizontal and vertical attitude deviation prediction values. At the same time, the model automatically outputs quantitative evaluation indexes such as mean absolute error (MAE), root mean square error (RMSE), and coefficient of determination ($R^2$), which are used to intuitively evaluate the fitting effect, prediction accuracy and reliability of the basic model, and provide a reference for subsequent input parameter optimization, model structure optimization and performance improvement.

## 3. Results and Analysis

The engineering data were divided into training set, test set and validation set according to the ratio of 8 : 1 : 1. The mean absolute error (MAE), root mean square error (RMSE) and determination coefficient ($R^2$) were used to evaluate the performance of the model. The smaller the MAE and RMSE, the smaller the prediction deviation, and the closer the $R^2$ to 1, the higher the model fitting effect and prediction accuracy.

### *3.1 Prediction Results*

Before the parameter optimization, the random forest basic prediction model is constructed with all the primary input variables. The prediction results of the model on the test set are shown in Table 1.

It can be seen from the table that the basic model can effectively predict the shield attitude deviation, and the coefficient of determination reaches 0.826, indicating that there is an obvious nonlinear correlation between the input parameters and the output deviation, and the random forest can better fit the relationship between the two. However, from the perspective of error indicators, MAE and RMSE are still high, indicating that the model has certain optimization space. The main reason is that the number of input parameters is large, there is information redundancy, and some parameters contribute less to the prediction results, resulting in limited generalization ability of the model.

**Table 1. Random Forest Model Prediction Results**

| evaluation index | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Random forest (RF) | 0.387 | 0.512 | 0.826 |

### *3.2 Input Parameter Optimization Results*

In this paper, the input parameters are optimized by eliminating the low contribution parameters one by one. Based on $R^2$, MAE and RMSE, the parameters with weak influence on the prediction results are eliminated, and the optimal input parameter combination is finally obtained. The comparison of model performance before and after parameter optimization is shown in Table 2.

**Table 2. Performance Comparison of the Model before and after Parameter Optimization**

| RF | MAE | RMSE | $R^2$ |
|---|---|---|---|
| Before optimization | 0.387 | 0.512 | 0.826 |

| | | | |
|---|---|---|---|
| optimized | 0.262 | 0.341 | 0.917 |

It can be clearly seen from the data in the table that after the optimization of input parameters and the removal of redundant features, the performance indexes of the model are significantly improved : the mean absolute error (MAE) is reduced from 0.387 before optimization to 0.262, with a decrease of 32.0 %. The root mean square error (RMSE) decreased from 0.512 to 0.341, with a decrease of 33.4 %. The coefficient of determination $R^2$ increased from 0.826 to 0.917, with an increase of 11.0 %. Among them, the significant decrease of MAE indicates that the average deviation between the model prediction results and the real values is significantly reduced, and the prediction stability is stronger. The significant decrease of RMSE shows that the sensitivity of the model to extreme deviation and abnormal samples decreases, and the anti-interference ability and robustness are significantly improved. R 2 is closer to 1, which indicates that the optimized model can better capture the nonlinear correlation between construction parameters and shield attitude deviation, and the fitting degree and interpretation ability are greatly enhanced.

The above results fully show that there are a large number of redundant features with low contribution to attitude prediction and high information overlap in the original full-parameter input. These features will introduce data noise, increase the computational burden of the model and reduce the generalization performance. By successively eliminating the low contribution parameters and retaining the key influence factors, the input dimension of the model can be effectively simplified and the noise interference can be weakened, so that the model can focus more on the essential mapping relationship between the core parameters and the output target, thus significantly improving the learning efficiency, prediction accuracy and engineering applicability. It is fully verified that the parameter optimization strategy adopted in this paper has a significant effect on the optimization of the random forest model, which can provide reliable support for the high-precision prediction of shield construction attitude.

*3.3 Impact Analysis of Key Parameters*

The influence of each input parameter on the attitude deviation is obtained by sorting the importance of the parameters, and the results are shown in Table 3. In this paper, after completing the basic model training, the feature importance score is used as the screening basis, and the input parameter optimization is carried out by successively eliminating the low contribution parameters, synchronously re-optimizing the hyperparameters, and repeatedly verifying the model performance: first, the importance scores of all the primary parameters are calculated. After eliminating the parameters with the lowest score, the random forest hyperparameters are re-adjusted and the model is trained to compare the changes of key indicators such as MAE, RMSE, and $R^2$. The iterative process of ' importance calculation-single parameter elimination-hyperparameter optimization-model training-accuracy evaluation ' is repeated, and the features with high redundancy and weak contribution to prediction are gradually eliminated until the model performance is no longer significantly improved, and the optimal input parameter combination is finally determined.

From the results of parameter importance ranking, it can be seen that the total thrust, cutterhead torque and earth pressure are the top three key parameters affecting the shield attitude deviation. The importance of the three accounts for nearly 50 % of the total, and plays a leading role in all input parameters. The total thrust directly determines the thrust force and direction control ability of the shield, and the uneven distribution of thrust can easily lead to horizontal and vertical deviations. The cutterhead torque reflects the cutterhead cutting load and stratum resistance state, and the sudden change of torque will aggravate the shield attitude fluctuation. The pressure of the soil bin directly affects the stability of the tunnel face and the force balance of the shield, and the pressure fluctuation will significantly change the trend of the excavation axis. The results show that in the actual construction, the total thrust, cutterhead torque and earth pressure are taken as the core monitoring objects and fine linkage control is carried out, which can reduce the risk of attitude deviation from the source and significantly improve the accuracy of tunnel alignment control and tunneling stability.

**Table 3. Proportion of Importance of Parameters**

| parameter | gross thrust | cutterhead torque | chamber earth pressure | feed preparation unit speed | other parameters |
|---|---|---|---|---|---|
| *Importance ratio* | *18.72%* | *16.35%* | *14.21%* | *10.74%* | *12.68%* |

*3.4 Comprehensive Analysis*

By constructing a random forest model and optimizing the input parameters by successive elimination, the high-precision prediction of shield attitude deviation is realized. The results show that : 1) Random forest is suitable for multi-factor coupling prediction of shield attitude; 2) Parameter optimization can significantly reduce model redundancy and improve prediction accuracy; 3) The total thrust, torque and earth pressure are the core parameters of attitude control. 4) The optimized model R 2 exceeds 0.9, which can meet the actual use requirements of the project.

## 4. Conclusion

In this paper, the prediction of shield attitude deviation is taken as the research goal. The random forest algorithm is used to construct the prediction model, and the lightweight and accuracy improvement of the model are realized by optimizing the input parameters. The main research conclusions are as follows :

(1) The random forest model is established by taking the total thrust, cutterhead torque, earth pressure, shield tail clearance, propulsion speed and other construction parameters as input and attitude deviation

as output, which can effectively realize nonlinear fitting and high-precision prediction. After parameter optimization, the coefficient of determination $R^2$ of the model can reach 0.917, which is significantly higher than that of the full-parameter basic model, indicating that parameter screening can effectively eliminate redundant information and reduce noise interference.

(2) Model error analysis shows that the optimized random forest model is significantly better than the full parameter model in MAE, RMSE and other indicators. The predicted value is more consistent with the true value, and the adaptability to extreme working conditions is stronger, which can meet the needs of the engineering site for attitude deviation prediction.

(3) The importance analysis of parameters shows that the total thrust, cutterhead torque and soil pressure have the most significant influence on the attitude deviation. In the actual construction, the key monitoring and fine control of the above parameters can effectively improve the level of linear control.

## References

DING, H. Y. (2016). Research on the attitude and trajectory control of shield machine based on BP neural network. *Machine Design and Manufacturing Engineering*, *45*(12), 46-49..

HU, C. M., LI, L., MEI, Y. et al. (2021). Global sensitivity analysis on parameters of the prediction model for shield vertical attitude. *Modern Tunnelling Technology*, *58*(2), 127-134.

KUWAHARA, H., HARADA, M., SENO, Y. et al. (1988). Application of fuzzy reasoning to the control of shield tunnelling. *Doboku Gakkai Ronbunshu*, *1988*(391), 169-178.

SHEN, X., & YUAN, D. J. (2020). Influence of shield yawing angle variation on shield-soil interaction. *China Journal of Highway and Transport*, *33*(3), 132-143.

WU, H. M., CHANG, J. Q., LI, G. et al. (2021). Prediction of driving posture and optimization of construction parameters for shield based on support vector machine. *Tunnel Construction*, *41*(Suppl.1), 11-18.

XIAO, H., XING, B., WANG, Y. et al. (2021). Prediction of shield machine attitude based on various artificial intelligence technologies. *Applied Sciences*, *11*(21), 10264.