ISSN: 1813-4890

# Surface settlement prediction for rectangular pipe jacking tunnel using machine learning algorithms with PSO-LSSVM

Rong Hu [1], Yongsuo Li [1,2,*], Kunpeng Wei [1], Min Tan [1], Jingting Xiao [1]

[1] School of Civil Engineering, Hunan City University, Yiyang 413002, China;

[2] Hunan Engineering Research Center of Structural Safety and Disaster Prevention for Urban Underground Infrastructure, Hunan City University, Yiyang 413002, China.

## Abstract

**This study investigates the prediction of ground settlement induced by rectangular pipe jacking tunnel excavation using four machine learning (ML) algorithms. The settlement database was derived from the Liu Ye Avenue West Extension Project in Hunan Province, comprising 104 data indicators from the right tunnel section, including jacking force, excavation speed, grouting pressure, and settlement values. Among these, 80 data indicators were selected as input parameters for the ML models. Hyperparameter tuning based on particle swarm optimization (PSO) was employed to effectively explore the optimal combination and enhance prediction performance. The performance of the ML models was evaluated by comparing the mean squared error (MSE), mean absolute error (MAE), and coefficient of determination ($R^2$). Results indicated that the PSO-LSSVM model outperformed other models in terms of surface settlement prediction accuracy and generalization ability, with MSE, MAE, and $R^2$ values of 0.367, 0.424, and 0.941, respectively.**

## Keywords

**Machine Learning, Particle Swarm Optimization, The Least Squares Support Vector Machine, Ground Surface Settlement.**

## 1. Introduction

With the continuous advancement of urbanization in China, the development of urban underground space has been further promoted to alleviate the tension of urban land use and traffic congestion. The length of subway lines has even reached one-third of the total operating mileage[1]. During tunnel excavation, ground settlement induced by tunneling may cause significant damage to existing structures. With the rapid development of artificial intelligence, machine learning algorithms, as a method for exploring the intrinsic relationships and patterns within data, have provided more valuable solutions for predicting ground deformation during shield tunnel construction. In a typical machine learning task, a model is designed to learn from a large amount of input data and attempt to predict future data or classify the data in a meaningful way[2].

Chen[3] et al. established an optimized support vector machine (SVM) prediction model for forecasting surface deformation of subway tunnels adjacent to large deep excavations, demonstrating that machine learning–based deformation prediction remains highly accurate under complex surrounding environmental conditions. Wang[4] et al. developed a surface settlement prediction controller using least squares support vector machines (LSSVM) and particle swarm optimization (PSO), with real-time shield tunneling parameters as inputs and surface settlement as the output. This approach ultimately confined construction disturbances within permissible limits. Inkoom[5] et al. estimated the accuracy, relative deviation, and precision of predictions made by each model for response variables in machine learning models such as Bayesian prediction, providing guidance for our research on machine learning algorithms. Guan[6] et al. employed the synthetic minority over-sampling technique (SMOTE) to augment the database and compared four machine learning algorithms, concluding that the optimal model exhibited good predictive performance for ground settlement during shield tunneling. As an alternative approach, the use of various machine learning algorithm models for ground settlement analysis offers new insights for the design and construction of tunnels and underground projects, as shown in Table 1.

Table 1 Application of machine learning algorithms in the prediction of land subsidence

| Cite | Machine learning algorithms | Dataset size | Evaluation indicators |
|---|---|---|---|
| Ding[7](2021) | MT-InSAR,LSTM | 33 samples | RMSE,R2 |
| Wang[8](2022) | BP,GRNN, RBF,Elman | Different sections of the metro tunnel | RMSE |
| Jiang[9](2023) | MRF-GCN | Long-term surface subsidence monitoring network with 64 monitoring sites | RMSE,R2 |
| Wang[10](2023) | EMD,CASSA,ELM, | Metro shield tunnel | RMSE |

To date, there remains no definitive method to determine which algorithm is best suited for predicting tunnel settlement. Generally, the performance of algorithm models is improved by tuning the hyperparameters of different algorithms. Therefore, it is worthwhile to investigate the performance comparison of various machine learning algorithms in the same case study, given the lack of robust training in existing machine learning–based settlement prediction models. Focusing on tunnel settlement prediction, this study integrates an improved intelligent optimization algorithm (PSO) with least squares support vector machines (LSSVM). Relying on real-time monitoring data from the rectangular pipe jacking tunnel construction of the West Extension of Liu Ye Avenue, a PSO-LSSVM surface settlement prediction model is established, with the expectation of providing theoretical support and technical reference for surface settlement prediction of similar shield tunnels.

## 2. Machine Learning Algorithms

This work introduces four widely used artificial intelligence algorithms: Random Forest (RF), Support Vector Machine (SVM), Support Vector Regression (SVR), and Backpropagation Neural Network (BPNN). Additionally, the Particle Swarm Optimization (PSO) algorithm is integrated into the BP neural network and the least squares–enhanced SVM model to optimize their hyperparameters.

### 2.1. Least Squares Support Vector Machine Algorithm

The Least Squares Support Vector Machine (LSSVM) modifies the traditional Support Vector Machine (SVM) by replacing the inequality constraints with equality constraints and employing the sum of squared errors as the loss function for the training dataset. This transformation converts the quadratic programming problem into solving a set of linear equations, thereby enhancing the computational speed and convergence accuracy. As an improved SVM based on statistical learning theory, LSSVM possesses a robust theoretical framework that simplifies the solution of quadratic optimization problems into solving linear equations. Consequently, it has been successfully applied in various fields, including data regression, pattern recognition, and time series forecasting.

Given the training data $\{(x_i,y_i)\}i=1N$, where $x_i \in Rd$ is the $d$-dimensional input vector, $y_i \in R$ is the corresponding output, and $N$ is the total number of training samples, the input space is mapped to the feature space using a nonlinear function $\phi(x_i)$. The form of the nonlinear function estimation model is as follows:

$$f(x) = \omega^T \varphi(x_i) + b \tag{1}$$

Based on the principle of structural risk minimization, the evaluation problem is formulated as an optimization problem:

$$\min_{\omega,b,e} J(\omega, e) = \frac{1}{2}\omega^T \omega + c\frac{1}{2}\sum_{i=1}^{N} e_i^2 \tag{2}$$

where $b$ is the bias term; $w$ is the weight vector of the hyperplane; $J$ represents the cumulative sum of the error and regularization parameters; $C$ is the penalty coefficient; $e$ is the error vector; and $e_i$ denotes the error quantity for the $i$-th sample.

## 2.2. PSO-LSSVM Algorithm

The key steps of the PSO-LSSVM algorithm include the initialization of the particle swarm, calculation of the fitness function, updating of particle positions and velocities, and updating of the global optimal solution. During the initialization phase, a set of particles is randomly generated, and each particle is assigned an initial position and velocity. The fitness function is employed to evaluate the quality of the solution for each particle, typically using indicators such as cross-validation error or classification accuracy. The updating of particle positions and velocities is adjusted based on their current positions and velocities as well as the global optimal solution. The flowchart of the algorithm is shown in Fig. 1.

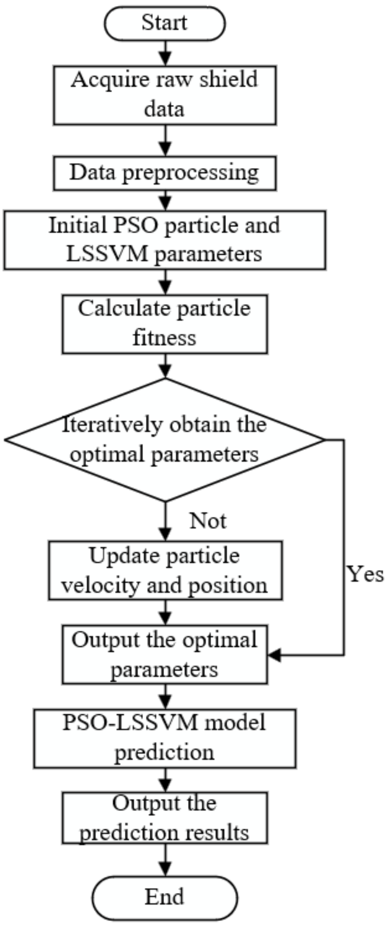


Fig.1 PSO-LSSVM flow chart

ISSN: 1813-4890

### 2.3. Hyperparameter selection

The hyperparameter settings for the four machine learning models are presented in the following Table 2.

Table 2 Hyperparameter selection

| Algorithmic models | Hyperparameter settings | Valid values |
|---|---|---|
| SVM | c | 1 |
| | gamma | 1 |
| BP | learning_rate | 0.03 |
| | hidden_dim | 20 |
| | loss | 0.001 |
| PSO-BP | learning_rate | 0.025 |
| | learning_rate | 20 |
| | loss | 0.001 |
| PSO-LSSVM | c | 4.483 |
| | gamma | 0.101 |
| | maxiter | 2000 |

## 3. Engineering Case Analysis

The construction of Liu Ye Avenue adopted the manufacturing process of "oblique intersection, oblique construction, and perpendicular jacking." The frame bridge was constructed using a working pit, a back wall, a sliding plate, and an on-site erected shield support frame. The frame bridge intersects with the Changzhang Expressway at an angle of 63.881°, with a cover soil thickness ranging from approximately 2.000 to 2.683 m above the bridge. During the construction process, normal traffic on the expressway could not be interrupted. However, jacking operations would inevitably cause ground disturbances and induce settlements. Excessive settlement could compromise traffic safety. Therefore, it was essential to arrange monitoring points on the road surface. To ensure that the frame bridge met the required standards during construction and to guarantee construction safety, monitoring points were strategically placed at key locations on the frame bridge and the steel shield.

## 4. Database Construction

To predict ground settlement for rectangular pipe jacking tunnels, this study proposes an intelligent analysis framework based on Python, which includes Support Vector Machine (SVM), Backpropagation Neural Network (BPNN), and Particle Swarm Optimization (PSO) algorithms. The framework, as illustrated in Fig. 2, consists of three stages: data acquisition and preprocessing, model establishment, and error analysis.

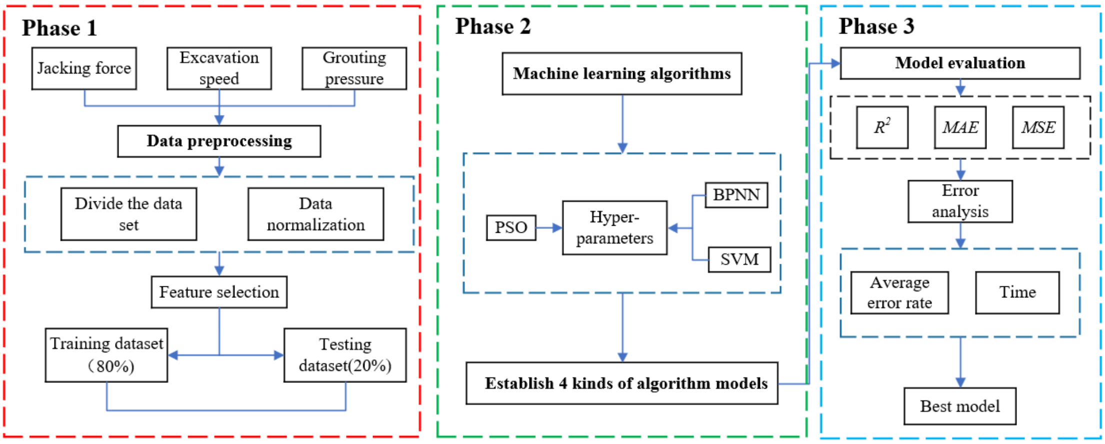


Fig. 2 General Frame Diagram

### 4.1. Input Parameter Selection

Currently, although scholars have proposed single-pipe jacking settlement formulas based on Mindlin solutions and random media theory to predict surface settlement for multiple pipe jacking operations[11], few studies have focused on utilizing machine learning algorithms to analyze and predict surface settlement. The data for this study were obtained from the monitoring data of the construction site of Liu Ye Avenue in Changde City, Hunan Province, where the tunnel was constructed using the pipe jacking method. The database for this study comprises two jacking variables and one grouting variable, totaling 26 sets of data. Each set of data is updated in real-time by the jacking equipment and covers the parameter range for each variable. In this study, the first 80% (i.e., the first 20 sets) are planned to be used as the training set, while the remaining 20% (i.e., the last six sets) are used as the prediction set for forecasting. The specific dataset is shown in Table 3.

Table 3 Data set

| Variable | Parameter type | Data | | | |
|---|---|---|---|---|---|
| | | Min. | Max. | Ave. | S.D. |
| Jacking force/KN | Input | 15601.47 | 48504.561 | 34586.2 | 9814.75 |
| Excavating velocity/(m/d) | Input | 0.825 | 1.985 | 1.64 | 0.223 |
| Grouting pressure/MPa | Input | 0.063 | 0.416 | 0.27 | 0.079 |
| Settlement value/mm | Output | -4 | 2 | -0.23 | 1.245 |

### 4.2. Data Preprocessing

Given the relatively small number of data sets but the large size of individual data points, normalization is essential. This process involves scaling the data to a specific range using a linear equation. Normalization enhances training efficiency and overall model accuracy by mitigating the impact of varying data scales. It also preserves data integrity, reduces the likelihood of data corruption, and prevents gradient explosion caused by excessively large numerical values. In this study, we continued the traditional machine learning approach of using gradient descent to compute the minimum fitness value. Through iterative updates of the gradient information in real-time, this method enables more accurate and efficient identification of the optimal parameter solutions.

## 5. Model Evaluation

The error metrics of the models are illustrated in Table 4 Among them, the PSO-LSSVM model exhibited a mean squared error ($MSE$) of 0.367, a mean absolute error ($MAE$) of 0.424, and a coefficient of determination ($R^2$) of 0.941. As shown in Table 4, the PSO-LSSVM model outperformed the PSO-BP model in terms of prediction accuracy. The lower $MAE$ value of the PSO-LSSVM model compared to other models indicates its superior fitting capability and strong generalization ability. Similarly, among the three traditional models, the BP neural network model demonstrated superior predictive performance but required longer computation time and exhibited some degree of overfitting. Overall, the PSO-LSSVM model was found to be significantly better than other models in terms of both accuracy and stability.

Generally, the complex interaction mechanisms between the pipe jacking machine and the strata, which give rise to nonlinear problems, can be effectively addressed using machine learning methods. These methods hold potential for application in predicting ground settlement and play an important role in improving construction efficiency, ensuring construction safety, and reducing construction costs.

Table 4 Error analysis data

| Algorithmic models | MSE | MAE | R2 | Time/s |
|---|---|---|---|---|
| PSO-LSSVM | 0.367 | 0.424 | 0.941 | 2.97 |
| PSO-BP | 1.023 | 0.437 | 0.904 | 3.67 |
| BP | 0.867 | 0.605 | 0.977 | 74.42 |
| SVM | 1.976 | 0.933 | 0.622 | 2.46 |

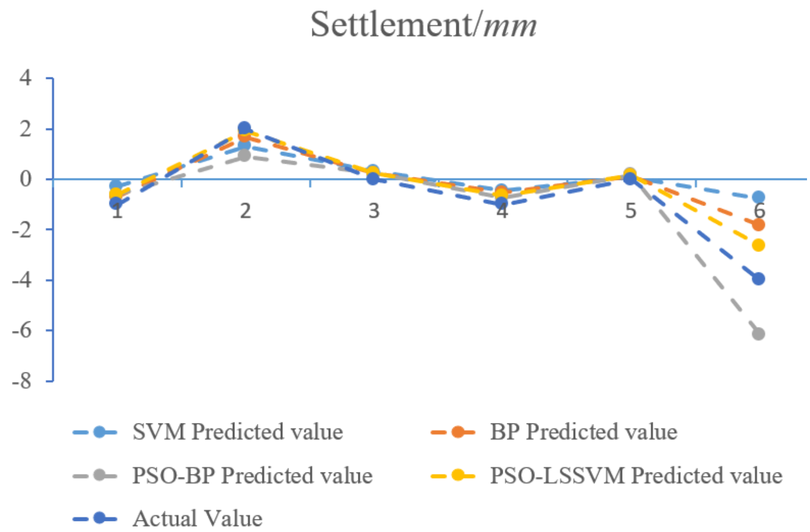


Fig. 3 Comparison chart of settlement predictions

## 6. Conclusion

In this study, data normalization was employed to mitigate the disparities between features, thereby preventing certain features from disproportionately influencing the model. This process also enhanced the convergence speed and accuracy of the model. Additionally, a comparative analysis was conducted between models with optimized hyperparameters and those without optimization. The results indicated that the optimal model, within a relatively short timeframe, outperformed other models in all metrics except for the coefficient of determination ($R^2$), which was 0.03 lower than that of the BP neural network. The optimized model demonstrated superior performance in predicting ground settlement. The SVM algorithm improved with particle swarm optimization (PSO) showed a 51% increase in accuracy and a decrease in error rate, along with enhanced generalization ability. The complex interaction mechanisms between the pipe jacking machine and the strata can be effectively addressed by intelligent models, which can handle the highly nonlinear nature of construction parameters and provide references for safe and efficient pipe jacking construction. Future work will focus on thoroughly investigating the interaction mechanisms between the pipe and the soil, and leveraging more engineering data to explore the application of artificial intelligence technologies in the field of tunnel settlement prediction.

## Acknowledgements

The authors sincerely acknowledge the vital facilities and resources provided by general project of Hunan college students' innovation training program (No. S202311527035). We are also grateful for the valuable contributions and insightful suggestions from Professor Hu Da, whose guidance has significantly enhanced the quality of this research. Additionally, we

ISSN: 1813-4890

appreciate the constructive comments from the anonymous reviewers, which have helped improve the clarity and robustness of this manuscript.

## References


[1] Guo S Y. Development and prospects of tunnel and underground engineering technology in China [J]. Modern Tunneling Technology, 2018, 55(S2): 1-14. (in Chinese)

[2] Jordan M I, Mitchell T M. Machine learning: Trends, perspectives, and prospects [J]. Science, 2015, 349(6245): 255-260.

[3] Chen X F, Liu L, Huang T. Research on settlement prediction methods for subway tunnels adjacent to large deep excavations [J]. Modern Tunneling Technology, 2014, 51(06): 94-100. (in Chinese)

[4] Wang P. Research on disturbance control of subway tunnel construction based on machine learning [J]. Modern Tunneling Technology, 2019. (in Chinese)

[5] Inkoom S, Sobanjo J, Barbu A, et al. Pavement crack rating using machine learning frameworks: Partitioning, bootstrap forest, boosted trees, Naïve bayes, and K-Nearest neighbors [J]. Journal of Transportation Engineering, Part B: Pavements, 2019, 145(3): 04019031.

[6] Guan H, Liu W, Wang F, et al. Prediction and application of ground settlement induced by shield tunneling based on data augmentation and machine learning algorithms [J]. Tunnel Construction (Chinese & English), 2022, 42(S1): 331-341. (in Chinese)

[7] Ding Q, Shao Z, Huang X, et al. Monitoring, analyzing and predicting urban surface subsidence: A case study of Wuhan City, China [J]. International Journal of Applied Earth Observation and Geoinformation, 2021, 102: 102422.

[8] Wang B, Zhang J, Zhang L, et al. Analysis and Prediction of Subway Tunnel Surface Subsidence Based on Internet of Things Monitoring and BP Neural Network [J]. Computational Intelligence and Neuroscience, 2022, 2022: 9447897.

[9] Jiang B, Zhang K, Liu X, et al. Prediction model with multi-point relationship fusion via graph convolutional network: A case study on mining-induced surface subsidence [J]. PLOS ONE, 2023, 18(8): e0289846.

[10] Wang Y, Dai F, Jia R, et al. A novel combined intelligent algorithm prediction model for the tunnel surface settlement [J]. Scientific Reports, 2023, 13(1): 9845.

[11] Jia P, Zhao W, Khoshghalb A, et al. A new model to predict ground surface settlement induced by jacked pipes with flanges [J]. Tunnelling and Underground Space Technology, 2020, 98: 103330.