Journal of Southeast University (English Edition) Vol. 39, No. 1, pp. 1 − 7 Mar. 2023 ISSN 1003—7985

# Back-analysis method of rock mass properties in tunnel engineering using multiple monitoring data based on LS-SVR algorithm

Li Zhaozhong[1,2] Chang Xiangyu[1] Wang Hao[1] Mao Jianxiao[1]

([1] Key Laboratory of Concrete and Prestressed Concrete Structures of Ministry of Education, Southeast University, Nanjing 211189, China)

([2] China Railway 24th Bureau Group Co., Ltd., Shanghai 200071, China)

**Abstract:** To accurately estimate the rock mass properties of a high-speed railway tunnel, a back-analysis method using multiple monitoring data based on the least-squares support vector regression (LS-SVR) algorithm is presented. The root mean square error (RMSE) and mean absolute percentage error (MAPE) are used as evaluation indices. The results of the parameter estimation are compared with those of the back propagation neural network (BPNN) and Gaussian process regression (GPR). The results show that for the single type of monitoring data, the LS-SVR model with vault settlement has the lowest RMSE and MAPE values. Moreover, as the data type increases, the RMSE value of the LS-SVR decreases, especially for the model with the mixed data of vault settlement, convergence, and floor heave. The comparison results show that the presented model has lower RMSE and MAPE values than BPNN and GPR. The LS-SVR model using multiple monitoring data shows better performance than existing back-analysis methods, improving the accuracy of the estimation of rock mass properties.

**Key words:** tunnel engineering; back-analysis method; rock mass properties; least-squares support vector regression algorithm

**DOI:** 10.3969/j.issn.1003 − 7985.2023.01.001

Complicated geological conditions (e.g., faults, high groundwater level, soft soil, and low overburden) exist in tunnel projects and could cause unexpected safety problems during construction[1]. The accurate estimation of rock mass properties is essential to simulate the actual geological environment and timely adjust the construction design. In general, in situ and laboratory tests can be used to estimate the properties of rock masses. However, a few laboratory-scale tests are inadequate to characterize these properties at large scales because of the inhomogeneity of rock mass[2-3]. Thus, the estimation of the accurate mechanical parameters of rock mass is needed for tunnel safety during construction.

Nowadays, the back-analysis method has been proven as one of the most useful methods in estimating the properties of rock and soil for the safe execution of underground structures[4-6]. For example, Gao et al.[7] estimated the mechanical parameters of the surrounding rock mass for a coal mine project using a neural network algorithm based on measurement convergence displacements. Wu et al.[8] identified the parameters of the rock mass properties based on field monitoring displacement data by employing an artificial neural network. Gao[9] presented an inverse back-analysis method for underground engineering using an evolutionary neural network, and the results show that the back-calculated parameters were in good agreement with the real values. These studies mainly focused on only using one type of monitoring data to estimate the rock mass parameters. Moreover, although satisfactory results were obtained, neural network algorithms generally need a large number of training samples to obtain satisfactory prediction accuracy. Thus, it is necessary to establish a more accurate estimation method for rock mass parameters.

In this study, a back-analysis method using multiple monitoring data based on the least-squares support vector regression (LS-SVR) algorithm is proposed to estimate rock mass properties. Seven combinations of multiple monitoring data are used to train the LS-SVR back-analysis model for estimating rock mass properties efficiently and accurately. A Yangshan high-speed railway tunnel is utilized to demonstrate the effectiveness of the presented approach. The conclusions could provide a reference for similar engineering problems.

## 1 Back-Analysis Method Based on LS-SVR

### 1.1 LS-SVR

LS-SVR is suitable for multi-output regression problems, especially when the outputs correlate with one another[10-11]. In this section, we provide a brief introduction to the basic principles of LS-SVR. The problem is

**Received** 2022-08-04, **Revised** 2023-01-05.

**Biographies:** Li Zhaozhong(1984—), male, Ph. D. candidate; Wang Hao (corresponding author), male, doctor, professor, wanghao1980@seu.edu.cn.

**Foundation items:** The National Natural Science Foundation of China (No. 51978155), the Science and Technology Program of Ministry of Housing and Urban-Rural Development (No. 2020-K-125).

**Citation:** Li Zhaozhong, Chang Xiangyu, Wang Hao, et al. Back analysis method of rock mass properties in tunnel engineering using multiple monitoring data based on LS-SVR algorithm[J]. Journal of Southeast University (English Edition), 2023, 39(1): 1 − 7. DOI: 10.3969/j.issn.1003 − 7985.2023.01.001.

regarded as finding the mapping between an input vector $\boldsymbol{x} = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_n\}^{\mathrm{T}}$ and an output vector $\boldsymbol{y} = \{y_1, y_2, \dots, y_n\}^{\mathrm{T}}$, where $n$ is the number of samples. LS-SVR solves this regression problem by finding a normal vector $\boldsymbol{w} = \{w_1, w_2, \dots, w_n\}$ and a displacement term $b$ that minimize the objective function with constraints[10]:

$$\begin{aligned} &\min \frac{1}{2}\|\boldsymbol{w}\|^2 + C\frac{1}{2}\boldsymbol{\varepsilon}^{\mathrm{T}}\boldsymbol{\varepsilon} \\ &\text{s.t.}\quad y_i = (w_i\kappa(\boldsymbol{x}, \boldsymbol{x}_i)) + b + \varepsilon_i \\ &\qquad\ \ i = 1, 2, \dots, n \end{aligned} \tag{1}$$

where $\kappa(\boldsymbol{x}, \boldsymbol{x}_i)$ represents a kernel function, $C$ is a positive real regularized parameter, and $\boldsymbol{\varepsilon} = \{\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n\}^{\mathrm{T}}$ denotes a vector of slack variables.

Because the deformation of the surrounding rock is nonlinear, the radial basis function (RBF) kernel function suitable for high-order nonlinear problems is adopted as follows[12]:

$$\kappa(\boldsymbol{x}, \boldsymbol{x}_i) = \exp\left(-\frac{\|\boldsymbol{x} - \boldsymbol{x}_i\|^2}{r^2}\right) \tag{2}$$

where $r$ denotes the kernel parameter.

The Lagrangian function for Eq. (1) is

$$L(\boldsymbol{w}, b, \boldsymbol{\varepsilon}, \boldsymbol{\alpha}) = \frac{1}{2}\|\boldsymbol{w}\|^2 + C\frac{1}{2}\boldsymbol{\varepsilon}^{\mathrm{T}}\boldsymbol{\varepsilon} - \boldsymbol{\alpha}^{\mathrm{T}}(\boldsymbol{w} + b + \boldsymbol{\varepsilon} - \boldsymbol{y}) \tag{3}$$

where $\boldsymbol{\alpha} = \{\alpha_1, \alpha_1, \dots, \alpha_n\}^{\mathrm{T}}$ represents a vector consisting of Lagrange multipliers.

The following linear system can be computed by solving Eq. (3)[13]:

$$\begin{bmatrix} 0 & \boldsymbol{I}_n^{\mathrm{T}} \\ \boldsymbol{I}_n & \boldsymbol{H} \end{bmatrix}\begin{bmatrix} b \\ \boldsymbol{\alpha} \end{bmatrix} = \begin{bmatrix} 0 \\ \boldsymbol{y} \end{bmatrix} \tag{4}$$

where $\boldsymbol{H} = \boldsymbol{\Omega} + \frac{1}{C}\boldsymbol{I}_n$ denotes a positive definite matrix; $\boldsymbol{\Omega}$ is defined by its elements $\omega_{i,j} = \kappa(\boldsymbol{x}_i, \boldsymbol{x}_j)\,(j = 1, 2, \dots, n)$; and $\boldsymbol{I}_n = \{1, 1, \dots, 1\}^{\mathrm{T}}$ represents a constant vector with $n$ terms.

The solutions of Eq. (4) are an optimal vector of Lagrange multipliers $\boldsymbol{\alpha}^* = \{\alpha_1^*, \alpha_2^*, \dots, \alpha_n^*\}^{\mathrm{T}}(\alpha_n^* \neq 0)$ and an optimal displacement term $b^*$. Then, the decision function of this problem is

$$f(\boldsymbol{x}) = \alpha_i^*\kappa(\boldsymbol{x}, \boldsymbol{x}_i) + b^* \tag{5}$$

### 1.2 Evaluation metrics

In this study, the root mean square error (RMSE) and mean absolute percentage error (MAPE) are used to evaluate the model performance. Specifically, the smaller the RMSE and MAPE, the more accurate the model. They are described as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{l}\sum_{k=1}^{l}(y_k - \hat{y}_k)^2} \times 100\% \tag{6}$$

$$\mathrm{MAPE} = \frac{1}{l}\sum_{k=1}^{l}\left|\frac{\hat{y}_k - y_k}{y_k} \times 100\%\right| \tag{7}$$

where $y_k$ and $\hat{y}_k$ stand for the actual and estimated values at the $k$-th term, respectively, and $l$ is the number of testing samples.

### 1.3 Back-analysis technique using LS-SVR

To identify the properties of the rock mass using multiple monitoring data, a back-analysis method based on LS-SVR is proposed. The steps of the presented method are described as follows:

1) Select appropriate property parameters for the rock mass and determine the lower and upper bounds of these parameters.

2) Perform the numerical model using randomly generated parameters within the predefined scale, and store the calculated response in the dataset.

3) Normalize the dataset between 0 and 1 and split it into a training set and a testing set. Train the back-analysis model based on the LS-SVR algorithm based on evaluation metrics, and use the grid search method to search for the optimum hyperparameters (i. e., the positive real regularized parameter $C$ and RBF kernel parameter $r$) of the LS-SVR.

4) Establish the LS-SVR model using the optimum hyperparameters. Input field monitoring data into the established model and calculate the mechanical parameters of the rock mass.

5) Perform the numerical model using the mechanical parameters, and compare the results with the field monitoring data.

## 2 Applications

### 2.1 Project description and monitoring data

The Yangshan high-speed railway tunnel, with a length of 850 m and a maximum overburden depth of 120 m, is used to illustrate the proposed method. The excavation of this tunnel started in 2019 using the New Austrian Tunneling Method. The tunnel is supported by radial rock bolts with a length of 5 m and a concrete lining with a thickness of 0.2 m. The shallow section is approximately 100 m with a rock mass of grade V, and it is comprised of strongly weathered zones and shattered fault zones. The monitoring data are important information during construction that directly reflect the tunnel status. An automatic monitoring system is installed to obtain the monitoring data. The typical cross-section and measuring points are shown in Fig. 1.

### 2.2 Numerical model and parameters

A finite difference model for the shallow section of the Yangshan tunnel is simulated by FLAC 3D. The rock mass

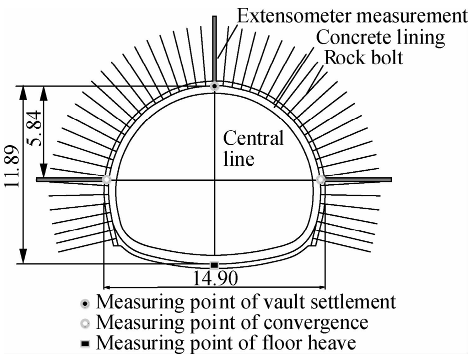


**Fig. 1** Typical cross-section and measuring points of the Yangshan tunnel (unit: m)

of the shallow section is grade V, which indicates that it has similar rock conditions and properties. The numerical model is chosen to be 100 m × 100 m × 40 m to reduce the boundary effect[14–15]. To obtain realistic model results, numerical simulation steps are performed according to the real construction sequences. The parameters of the tunnel support system are determined based on previous studies[13, 16]. Rock bolts are modeled as cable elements, and Young's modulus and Poisson's ratio of the rock bolts are 210 GPa and 0. 3, respectively. The concrete lining is modeled as the shell element, and Young's modulus and Poisson's ratio of the lining are 29 GPa and 0. 2, respectively. Regarding the boundary conditions, the normal movements on all sides of the 3D model are restrained, whereas the bottom of the model is not allowed to move in the three directions. Fig. 2 presents the case of the numerical model and measuring points for the back analysis.

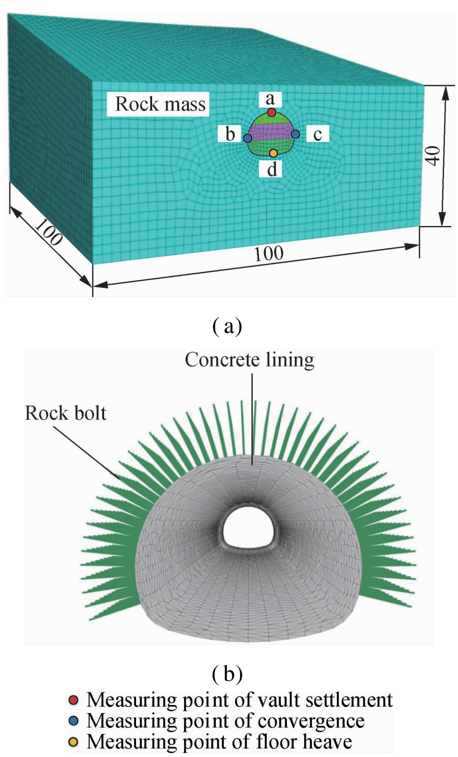


**Fig. 2** Finite difference model of the Yangshan tunnel and measuring points. (a) Finite difference model (unit: m); (b) Tunnel support system

For the properties of the rock mass, the Mohr-Coulomb failure model is used to model the rock mass. Tab. 1 lists the ranges of the parameters that are based on preliminary geotechnical studies of the predominant rock types encountered at the tunnel site.

**Tab. 1** Lower/upper bounds of the rock mass parameters

| Density/ ($kg \cdot m^{-3}$) | Young's modulus/MPa | Poisson's ratio | Cohesion/ kPa | Friction angle/ (°) |
|---|---|---|---|---|
| 1 900-2 100 | 50-500 | 0. 2-0. 3 | 80-120 | 25-35 |

To ensure construction safety, the monitoring data are recorded over 30 d. The monitoring data are used as input to the back-analysis technique of LS-SVR. Fig. 3 shows the monitoring data with tunnel face advancement. To verify the accuracy of the finite difference model, a verification case is conducted. Initial values of the rock mass parameters correspond to the average values of their parameter ranges. Fig. 3 also shows the comparison between the numerical solution and measuring data at the same location. Evidently, significant residuals exist,

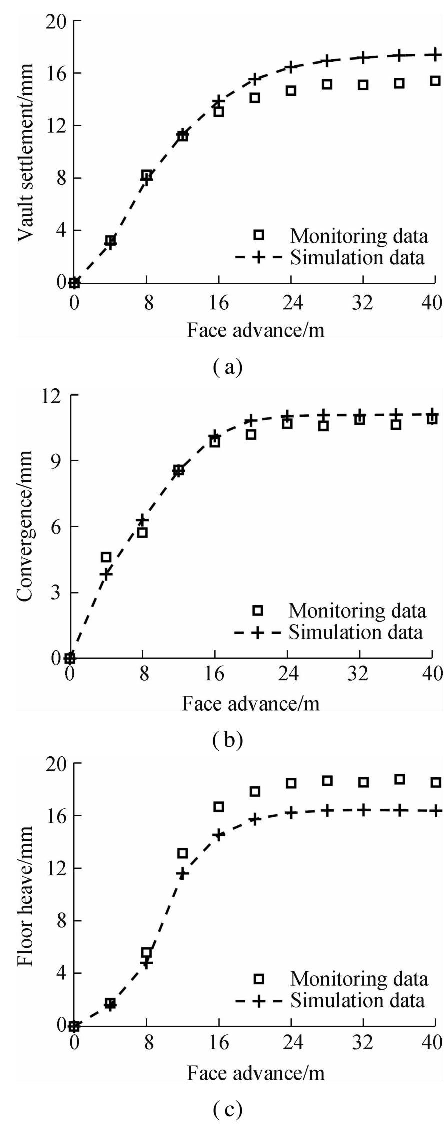


**Fig. 3** Monitoring and simulation data of the Yangshan tunnel. (a) Vault settlement; (b) Convergence; (c) Floor heave

which means that it is necessary to employ the back-analysis technique to make the values of the rock mass parameters close to real ones.

### 2.3 Parameter back analysis with multiple monitoring

The numerical model with random rock mass parameters in the given ranges is run 130 times to prepare the training samples[17]. Each numerical model is executed for 30 d, and the monitoring data of the vault settlement, convergence, and floor heave is recorded. Then, the monitoring data collected during construction is inputted into the LS-SVR model to estimate the rock mass properties.

To obtain accurate rock mass properties, seven combinations of multiple monitoring data are used to train the LS-SVR model, including vault settlement (V), convergence (C), floor heave (F), mixed data of vault settlement and convergence (V + C), mixed data of vault settlement and floor heave (V + F), mixed data of convergence and floor heave (C + F), and mixed data of vault settlement, convergence, and floor heave (V + C + F). Tab. 2 shows the training results of the LS-SVR for the back analysis. For the single type of monitoring data, the LS-SVR model with vault settlement has the lowest RMSE value, which indicates that it shows the best performance. Moreover, as the data type increases, the RMSE value of the LS-SVR decreases, especially for the model with the mixed data of vault settlement, convergence, and floor heave. Hence, the mixed data can model the relationship between the monitoring data and rock mass properties with good satisfactory prediction accuracy.

**Tab. 2** Training results of the back-analysis model for seven combinations of multiple monitoring data

| Data type | V | C | ST | V + C | V + ST | C + ST | V + C + ST |
|---|---|---|---|---|---|---|---|
| RMSE | 0.10 | 0.13 | 0.11 | 0.04 | 0.05 | 0.07 | 0.02 |

Tab. 3 shows the estimation of rock mass properties for seven combinations of multiple monitoring data. A comparison between the monitoring data and predicted data from the back-analysis parameters from LS-SVR is shown in Fig. 4. The RMSE and MAPE values between the monitoring data and predicted data are shown in Fig. 5. As shown in Figs. 4 and 5, the predicted data exhibit a notably good agreement with the monitoring data for seven models. Moreover, the RMSE and MAPE values of the LS-SVR model with the mixed data of vault settlement, convergence, and floor heave are the lowest, which indicates that it exhibits its superiority in estimating rock mass properties.

### 2.4 Comparison of parameter estimation methods

To further verify the performance of the LS-SVR model, the backpropagation neural network (BPNN) and Gaussian process regression (GPR) will be used for the comparative purpose. The BPNN is a forward feedback network, and it is also the most commonly used neural network in underground structures[18]. A genetic algorithm (GA) is used to search for the optimum hyperparameter of the BPNN. GPR is a nonparametric probabilistic method to solve nonlinear functions[19]. Hence, GPR has also been applied in various studies for solving nonlinear problems in tunnel projects. All of these methods use the same learning settings as those proposed in this

**Tab. 3** Estimation of rock mass properties for seven combinations of multiple monitoring data

| Data type | Density/ (kg · m$^{-3}$) | Young's modulus/MPa | Poisson's ratio | Cohesion/ kPa | Friction angle /(°) |
|---|---|---|---|---|---|
| V | 2 004.68 | 234.13 | 0.265 4 | 105.80 | 28.83 |
| C | 2 013.35 | 237.21 | 0.241 6 | 89.86 | 29.18 |
| F | 2 004.40 | 241.32 | 0.253 2 | 104.54 | 30.22 |
| V + C | 2 014.18 | 248.90 | 0.270 4 | 90.41 | 29.31 |
| V + F | 2 010.09 | 241.23 | 0.264 7 | 97.56 | 29.87 |
| C + F | 2 014.47 | 245.01 | 0.246 6 | 90.80 | 29.70 |
| V + C + F | 2 017.56 | 239.76 | 0.269 6 | 98.37 | 28.85 |

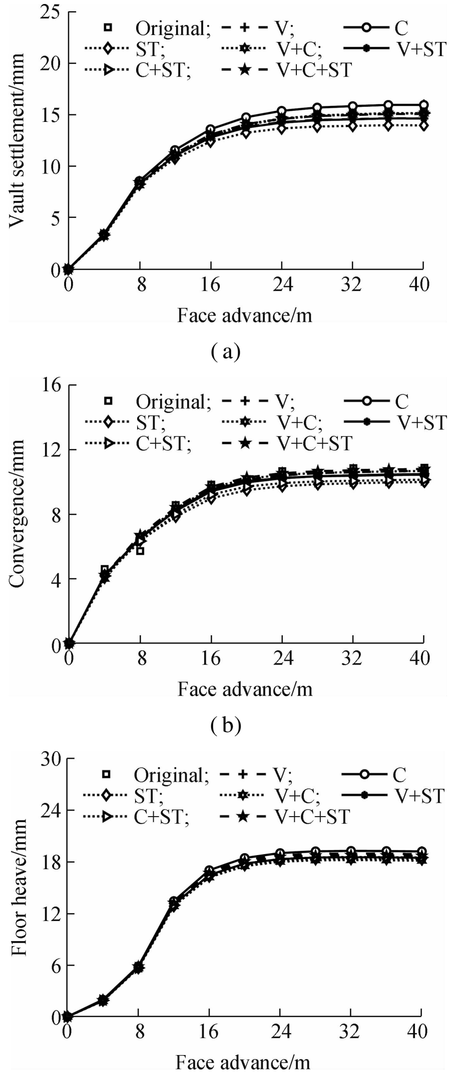


**Fig. 4** Comparison between the monitoring data and predicted data from the back-analysis parameters with seven combinations of multiple monitoring data. (a) Vault settlement; (b) Convergence; (c) Floor heave

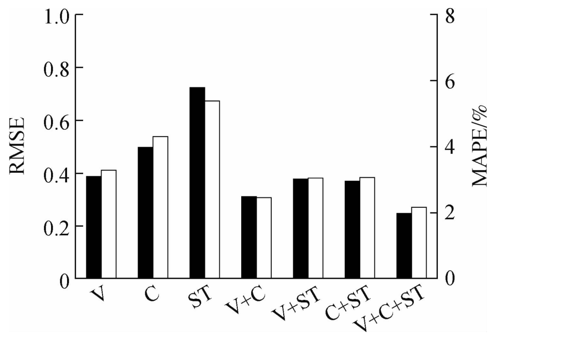


**Fig. 5** RMSE and MAPE of the monitoring data and predicted data for seven combinations of multiple monitoring data

paper. The training results and estimation results of rock mass properties are provided in Tabs. 4 and 5. As shown in Tab. 4, the RMSE values of GPR and the GA-BPNN are higher than those of LS-SVR. This finding proves that GPR and the BPNN usually require more training samples to improve their performance for nonlinear problems. Moreover, the LS-SVR model exhibits superiority over the other two methods.

**Tab. 4** Training results of the back-analysis model for the three models

| Data type | GA-BPNN | GPR | LS-SVR |
|---|---|---|---|
| Testing error | 0.05 | 0.03 | 0.02 |

**Tab. 5** Estimation results of the rock mass properties for the three models

| Data type | Density/(kg · m$^{-3}$) | Young's modulus/MPa | Poisson's ratio | Cohesion/kPa | Friction angle/(°) |
|---|---|---|---|---|---|
| GA-BPNN | 2 015.60 | 244.08 | 0.257 0 | 98.74 | 28.49 |
| GPR | 2 012.09 | 241.08 | 0.268 6 | 95.03 | 30.27 |
| LS-SVR | 2 017.56 | 239.76 | 0.269 6 | 98.37 | 28.85 |

A comparison between the monitoring data and predicted data from the back-analysis parameters from the three methods is shown in Fig. 6. To further quantify the performance of the methods, the RMSE and MAPE are also calculated and shown in Fig. 7. As shown in Figs. 6 and 7, the GA-BPNN has the poorest prediction results with the highest RMSE and MAPE values. Moreover, LS-SVR shows lower RMSE and MAPE values than GPR, which indicates that LS-SVR has better prediction accuracy. This is because LS-SVR exhibits superior generalization capacities for small sample datasets. Based on the results of the preceding analyses, LS-SVR is suitable for estimating rock mass properties.

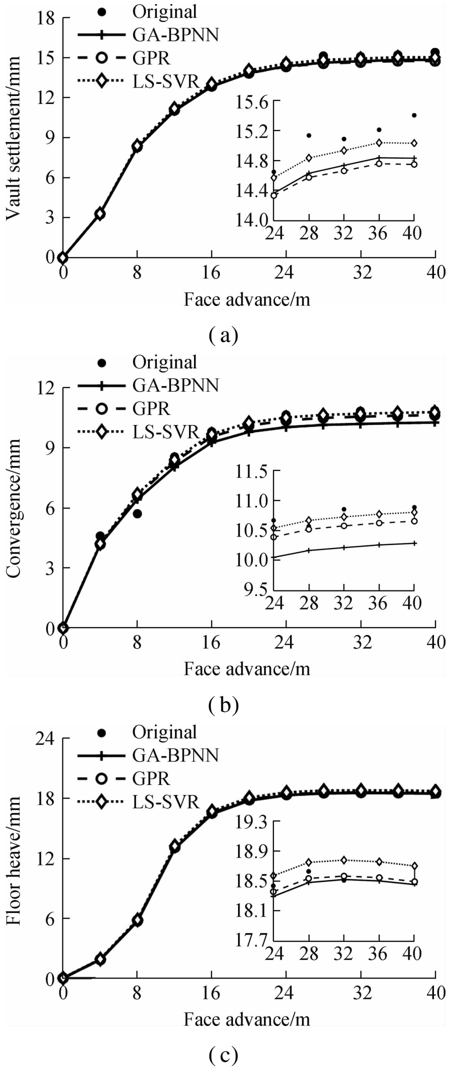


**Fig. 6** Prediction results of the monitoring data for the three models. (a) Vault settlement; (b) Convergence; (c) Floor heave

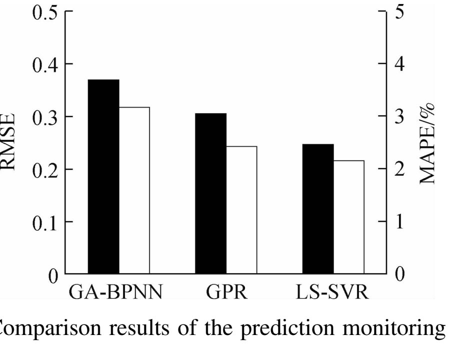


**Fig. 7** Comparison results of the prediction monitoring data for the three models

## 3 Conclusions

1) A back-analysis method using multiple monitoring data based on the LS-SVR algorithm is developed to estimate rock mass properties. A finite difference model is built and simulated to prepare training samples for the back-analysis LS-SVR model. Moreover, for the single type of monitoring data, the LS-SVR model with vault settlement has the lowest RMSE value, which indicates that it shows better performance.

2) As the data type increases, the RMSE value of the LS-SVR decreases, especially for the model with the mixed data of vault settlement, convergence, and

floor heave. Therefore, the mixed data can model the relationship between the monitoring data and rock mass properties with good satisfactory prediction accuracy.

3) To demonstrate the performance of the LS-SVR model, it is compared with BPNN and GPR. LS-SVR has better performance than the other two models. Hence, it is a suitable technique for estimating rock mass properties.

## References


[1] Chang X Y, Wang, H, Zhang Y M, et al. Bayesian prediction of tunnel convergence combining empirical model and relevance vector machine[J]. *Measurement*, 2022, **188**: 110621. DOI: 10.1016/j.measurement.2021.110621.

[2] Fakhimi A, Salehi D, Mojtabai N. Numerical back analysis for estimation of soil parameters in the Resalat Tunnel project[J]. *Tunnelling and Underground Space Technology*, 2004, **19**(1): 57 - 67. DOI: 10.1016/s0886 - 7798(03)00087 - 7.

[3] Gao W, Ge M M. Back analysis of rock mass parameters and initial stress for the Longtan tunnel in China[J]. *Engineering with Computers*, 2016, **32**(3): 497 - 515. DOI: 10.1007/s00366-015-0428-8.

[4] Sun P M, Bao T F, Gu C S, et al. Parameter sensitivity and inversion analysis of a concrete faced rock-fill dam based on HS-BPNN algorithm[J]. *Science China Technological Sciences*, 2016, **59**(9): 1442-1451. DOI: 10.1007/s11431-016-0213-y.

[5] Nikakhtar L, Zare S, Nasirabad H M, et al. Application of ANN-PSO algorithm based on FDM numerical modelling for back analysis of EPB TBM tunneling parameters [J]. *European Journal of Environmental and Civil Engineering*, 2020, **26**(8): 3169 - 3186. DOI: 10.1080/19648189.2020.1795725.

[6] Sun J L, Wang F, Wang X L, et al. A quantitative evaluation method based on back analysis and the double-strength reduction optimization method for tunnel stability [J]. *Advances in Civil Engineering*, 2021, **2021**: 8899685. DOI: 10.1155/2021/8899685.

[7] Gao W, Chen D L, Dai S, et al. Back analysis for mechanical parameters of surrounding rock for underground roadways based on new neural network[J]. *Engineering with Computers*, 2017, **34**(1): 25 - 36. DOI: 10.1007/s00366-017-0518-x.

[8] Wu Y K, Yuan H N, Zhang B Y, et al. Displacement-based back-analysis of the model parameters of the Nuozhadu High Earth-Rockfill Dam[J]. *Scientific World Journal*, 2014. DOI: 10.1155/2014/292450.

[9] Gao W. Inverse back analysis based on evolutionary neural networks for underground engineering[J]. *Neural Processing Letters*, 2016, **44**(1): 81 - 101. DOI: 10.1007/s11063-016-9498-x.

[10] Xu S, An X, Qiao X D, et al. Multi-task least-squares support vector machines[J]. *Multimedia Tools and Applications*, 2013, **71**(2): 699 - 715. DOI: 10.1007/s11042-013-1526-5.

[11] Li Z Z, Wang H, Chang X Y, et al. Prediction of surrounding rock convergence deformation of high speed railway tunnel based on combined model[J]. *Journal of Southeast University(Natural Science Edition)*, 2021, **51**(05): 851 - 858. DOI: 10.3969/j.issn.1001-0505.2021.05.017. (in chinese)

[12] Torabi-Kaveh M, Sarshari B. Predicting convergence rate of Namaklan twin tunnels using machine learning methods [J]. *Arabian Journal for Science and Engineering*, 2020, **45**(5): 3761 - 3780. DOI: 10.1007/s13369-019-04239-1.

[13] Zhu X Q, Gao Z H. An efficient gradient-based model selection algorithm for multi-output least-squares support vector regression machines[J]. *Pattern Recognition Letters*, 2018, **111**: 16 - 22. DOI: 10.1016/j.patrec.2018.01.023.

[14] Luo Y B, Chen J X, Chen Y, et al. Longitudinal deformation profile of a tunnel in weak rock mass by using the back analysis method[J]. *Tunnelling and Underground Space Technology*, 2018, **71**: 478 - 493. DOI: 10.1016/j.tust.2017.10.003.

[15] Kolivand F, Rahmannejad R. Estimation of geotechnical parameters using Taguchi's design of experiment(DOE) and back analysis methods based on field measurement data[J]. *Bulletin of Engineering Geology and the Environment*, 2017, **77**(4): 1763 - 1779. DOI: 10.1007/s10064-017-1042-3.

[16] Zhuang D Y, Ma K, Tang C A, et al. Mechanical parameter inversion in tunnel engineering using support vector regression optimized by multi-strategy artificial fish swarm algorithm[J]. *Tunnelling and Underground Space Technology*, 2019, **83**: 425 - 436. DOI: 10.1016/j.tust.2018.09.027.

[17] Wang H, Chang X Y, Zhang Y M, et al. Inversion analysis of mechanical parameters of surrounding rock in high-speed railway tunnel[J]. *Journal of Railway Engineering Society*, 2020, **37**: 47 - 53. DOI: 10.3969/j.issn.1006-2106.2020.09.009. (in Chinese)

[18] Fei J B, Wu Z Z, Sun X H, et al. Research on tunnel engineering monitoring technology based on BPNN neural network and MARS machine learning regression algorithm [J]. *Neural Computing &Applications*, 2021, **33**(1): 239 - 255. DOI: 10.1007/s00521-020-04988-3.

[19] Khatib T, Mohamed A, Sopian K, et al. Assessment of artificial neural networks for hourly solar radiation prediction [J]. *International Journal of Photoenergy*, 2012, **2012**: 946890. DOI: 10.1155/2012/946890.

# 基于 LS-SVR 算法的多源监测数据高铁隧道围岩参数反分析方法

李照众[1,2] 畅翔宇[1] 王 浩[1] 茅建校[1]

([1]东南大学混凝土及预应力混凝土结构教育部重点实验室,南京 210096)
([2]中铁二十四局集团有限公司,上海 200071)

**摘要:**为了准确估计岩体性质,依托阳山高速铁路隧道,提出了一种基于最小二乘支持向量回归(LS-SVR)的多源监测数据高铁隧道围岩参数反分析方法. 以均方根误差(RMSE)和绝对百分比误差(MAPE)为评价指标,将参数反分析结果与 BP 神经网络和高斯过程回归模型结果进行比较. 结果表明,对于单一类型的监测数据,考虑拱顶沉降的 LS-SVR 模型的 RMSE 和 MAPE 值最低. 随着监测数据类型的增加,LS-SVR 反分析模型的 RMSE 值逐渐减小,且采用拱顶沉降、收敛和仰拱隆起 3 种监测数据的反分析模型的 RMSE 值最小. 相比于 BP 神经网络和高斯过程回归模型,LS-SVR 模型具有较低的 RMSE 和 MAPE 值. 相较于现有围岩力学参数反分析方法,考虑多源监测数据的 LS-SVR 模型具有更高的参数反分析精度.

**关键词:**隧道工程;参数反分析方法;围岩力学参数;最小二乘支持向量回归算法

**中图分类号:**U456