Multi-objective optimization of tunnel displacement control construction parameters based on nonlinearity

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Abstract. In tunnel engineering, displacement and deformation monitoring is an important link, but monitoring data often presents complex nonlinear characteristics. Taking the construction of a highway tunnel as the background, based on the support vector machine algorithm, the variable rotation method is used to optimize its parameters, presenting the complex nonlinear characteristics of monitoring data and establishing a nonlinear model of tunnel displacement monitoring time series. Using this model to make accurate predictions of future displacement and deformation, scientifically guiding on-site monitoring and construction. The experimental results show that after constructing 15 time series as learning samples, rolling prediction is performed using 15 data as prediction samples. As can be seen, the maximum relative error of the prediction is 0.365%.

Keywords: tunnel engineering, support vector machine, variable rotation method, displacement prediction.

1 Introduction

Tunnel engineering is an indispensable and important component of modern urban development, and tunnel displacement control is one of the key factors to ensure tunnel construction safety and stable operation. Firstly, we need to understand the basic principles of tunnel displacement control. During tunnel construction, deformation and displacement of the soil are inevitable, and excessive displacement can lead to damage and safety hazards to the tunnel structure. Therefore, by adjusting construction parameters reasonably, such as support structures and soil consolidation, tunnel displacement can be effectively controlled, ensuring the safety and sustainable development of the project[1]. Traditional tunnel displacement control methods are mainly based on experience and expert experience, lacking scientific and systematic approaches. The multi-objective optimization method based on nonlinear tunnel displacement control construction parameters can fully consider the nonlinear characteristics of soil, optimize construction parameters through mathematical models and computer simulation, and make tunnel displacement control more accurate and reliable. When conducting multi-objective optimization of tunnel displacement control construction parameters, multiple objective functions need to be considered, such as minimizing displacement,

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minimizing support structure costs, and maximizing construction efficiency. There are certain contradictions and constraints between these objectives, so multi-objective optimization algorithms such as genetic algorithms, particle swarm optimization algorithms, etc. need to be used to adjust and balance parameters[2]. In addition, multi-objective optimization of tunnel displacement control construction parameters also needs to consider the influence of factors such as the mechanical properties of the soil, construction technology, and environmental factors. By collecting and analyzing relevant data, establish soil and construction models, and combine them with actual engineering situations to optimize parameters and design schemes. The multi-objective optimization of tunnel displacement control construction parameters has important application value in practical engineering. It can improve the safety and stability of engineering, reduce cost and resource waste, and improve the economic and environmental benefits of the project. However, there are still some challenges and difficulties in practical applications[3]. Firstly, the complexity and uncertainty of tunnel engineering make parameter optimization and scheme design more difficult. Secondly, the acquisition and processing of data is also a key issue that requires full consideration of the reliability and accuracy of the data. In addition, multi-objective optimization of tunnel displacement control construction parameters requires a large amount of calculation, and requires the use of tools such as computers and simulation software for auxiliary analysis and design. With the continuous development of engineering technology, the demand for optimizing construction parameters for tunnel displacement control is also increasing. This paper will explore the method and application of multi-objective optimization of tunnel displacement control construction parameters based on nonlinearity.

2 Introduction to Support Vector Machine Algorithm

The support vector machine algorithm mainly solves the problems of pattern recognition and function fitting. The following mainly explains the function fitting problem of support vector machines[4].

For the function fitting of support vector machines, let's start with linear fitting. Function $\mathrm{f(x) = wx + b}$, fit data $(x_i, y_i), i = 1,2,\dots,n, x_i \in R^n, y_i \in R$, considering the fitting error, introduce a relaxation factor ξ_i, and the error minimization expression of ξ_i^*SVM regression problem is as follows:

$$\mathrm{Min}\left\{\frac{1}{2}\mathrm{w}^2 - \mathrm{C}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\xi_i + \xi_i^*)\right\} \tag{1}$$

$$\mathrm{s.t.}\begin{Bmatrix} y_i - w \times x_i - b \le \varepsilon + \xi_i \\ w \times x_i + b - y_i \le \varepsilon + \xi_i^* \end{Bmatrix} \tag{2}$$

For this convex quadratic optimization problem, introduce the Lagrange function:

$$\mathrm{L(w,b,a,a*},\xi_i,\xi_i^*) = \frac{1}{2}\mathrm{w}^2 + \mathrm{C}\sum_{\mathrm{i=1}}^{\mathrm{n}}(\xi_i + \xi_i^*) - \sum_{\mathrm{i=1}}^{\mathrm{n}}\mathrm{a_i}(\varepsilon + \xi_i - y_i + w \times x_i + b) -$$

$$-\sum_{i=1}^{n}(\eta_i\xi_i+\eta_i^*\xi_i^*)-\sum_{i=1}^{n}a*_i(\varepsilon+\xi_i-y_i+w\times x_i+b) \quad (3)$$

In the formula: a, a * is the Lagrange multiplier.

The extreme value of the function satisfies:

$$\frac{\delta L}{\delta b}=\frac{\delta L}{\delta w}=\frac{\delta L}{\delta \xi_i}=\frac{\delta L}{\delta \xi_i^*}=0 \quad (4)$$

Thus,

$$f(x)=\sum_{i=1}^{n}(a_i-a*_i)(x_i\times x)+b \quad (5)$$

For nonlinear regression, the idea of SVM is to map data x to a high-dimensional feature space F through a nonlinear mapping Φ, and perform linear regression in this space, that is:

$$f(x)=(w\times\Phi(x))+b\ \Phi: R^n\rightarrow R^F \quad (6)$$

The regression function is obtained as:

$$f(x)=\sum_{i=1}^{n}(a_i-a*_i)(\Phi(x)\times\Phi(x_i))+b=\sum_{i=1}^{n}(a_i-a*_i)K(x_i,x)+b \quad (7)$$

In the formula:$K(x_i,x)$ is the kernel function, and any symmetric kernel function that satisfies the Mercer condition corresponds to the dot product of the feature space[5].

3 Tunnel displacement prediction model based on SVM

3.1 Selection of learning and testing samples

Using the arch monitoring data of a certain highway section as the original sample, each sample is two-dimensional, with the first variable being the measurement date and the second variable being the displacement value[6].

3.2 Model parameter selection

After determining the learning samples, the establishment of the displacement prediction model mainly depends on the selection of support vector machine parameters: kernel function, penalty function C, loss function, which have a significant impact on the accuracy and generalization ability of the prediction structure. This paper calculates the use of radial basis kernel functions and εinsensitive loss functions. Optimization of function parameters using variable rotation method:

(1) Initialize the value ranges of σ,ε and C, which are 1~30, 0.001~1, 1~400, respectively;

(2) Determine the initial values of σ,ε and C as 1,0.001,1;

(3) The variable C starts from 1 and increases in a cycle step size of 5, with a final value of 400. When c=145, the average error is the smallest;

(4) Given C=145, variable σ starts from 1 and grows with a cycle size of 1, with a final value of 30. When σ=2, the average error is the smallest;

(5) Taking C=145 and σ=2, the variable ε starts from 0.001 and increases with a cycle size of 0.0005, with a final value of 1. Regression calculation shows that the minimum average error is obtained when ε=0.005[7].

4 Engineering Examples

4.1 Project Overview

The surrounding rock types for tunnel crossing are Class III and IV, with Class III and IV surrounding rocks accounting for 45% and 55% of the total length. The maximum burial depth of the tunnel chamber is 38.0m, with a tunnel axis direction of 147 ° and a ridge direction of 56 °. The tunnel axis is perpendicular to the ridge direction. The uneven burial depth of the left and right tunnels belongs to a typical unsymmetrically loaded multi-arched tunnel.

4.2 Learning and Predicting Samples

The first 15 sets of data in the table below are learning samples, while the last 15 sets are used to test the predicted samples[8-10].

4.3 Fitting analysis

As shown in Figure 1, an SVM calculation program optimized by variable rotation method was developed using matlab. 15 time series were constructed as learning samples as shown in Table 1, and the last 15 data were used as prediction samples for rolling prediction. Table 2 shows that the maximum predicted relative error is 0.365%.

Table 1. The learning and testing samples

Date of measurement (d)	Vault sinking (mm)
2020- 12-7	0
2020-12-9	0.37
2020- 12-11	0.61
2020 -12-13	0.87
2020- 12-15	0.95
2020- 12-17	1.14
2020-12-19	1.21
2020-12-21	1.25
2020- 12-23	1.29
2020- 12-25	1.30
2020- 12-27	1.32
2020 - 12-29	1.33

Date of measurement (d)	Vault sinking (mm)
2020- 12-31	1.33
2021 -1-2	1.36
2021 -1 -4	1.36
2021-1-6	1.37
2021 -1 -8	1.39
2021- 1-10	1.40
2021-1-12	1.40
2021 -1-14	1.41
2021 -1-16	1.41
2021-1-18	1.41
2021 -1 -20	1.41
2021 - 1 -22	1.42
2021- 1-24	1.42
2021 -1-26	1.45
2021-1 -28	1.46
2021-1 -30	1.46
2021 -2-1	1.47
2021 -2-3	1.48

Table 2. Error analysis

Vault sinking (mm)	Regression forecast value (mm)	Error (%)
1.37	1.365	0.365
1.39	1.385	0.360
1.40	1.395	0.357
1.40	1.395	0.357
1.41	1.405	0.355
1.41	1.405	0.355
1.41	1.405	0.355
1.41	1.405	0.355
1.42	1.415	0.352
1.42	1.415	0.352
1.45	1.445	0.345
1.46	1.455	0.342
1.46	1.455	0.342
1.47	1.465	0.340
1.48	1.475	0.338

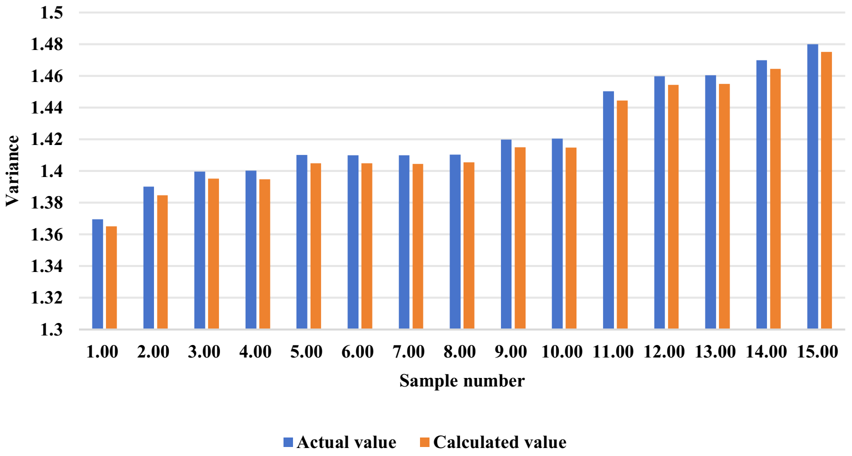

Fig. 1. Comparison between monitoring data and prediction data

5 Conclusion

The problem of fitting and predicting tunnel engineering monitoring data is essentially a function approximation problem between various variables. They often exhibit complex nonlinear characteristics, especially when it comes to multi variable, multi factor, and high-dimensional fitting. In addition, on-site monitoring often has discrete and intermittent characteristics, making the problem a small sample problem. Support vector machines do not require explicit function expressions and indirectly reflect the mapping relationships between various factors, effectively solving these bottleneck problems and possessing good generalization ability. This paper is based on the data of crown subsidence in highway tunnels and establishes a nonlinear prediction model based on improved SVM, which has a fast convergence speed and high accuracy, opening up a new path for the information construction of tunnel engineering.

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