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Multi-influencing Factor Weighted WPSO–SVM Prediction of Subway Tunnel Settlement under GRA Supports

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Abstract

With the rapid economic development and urbanization in China, subway systems have become the primary mode of urban rail transit. However, during subway operation, the tunnels may experience settlement and deformation due to various influencing factors. To guarantee safe operation of subway systems and eliminate potential safety hazards, tunnel settlement prediction has important significance. However, existing studies have seldom discussed the effects of weighting factors on subway tunnel settlement prediction. In addition, the optimization of support vector machine (SVM) using particle swarm optimization (PSO) often suffers from issues such as local optimization and premature convergence. To address these problems, grey relational analysis (GRA) and weighted particle swarm optimization (WPSO) SVM were combined, and a GRA-WPSO-SVM prediction model was constructed. This model was applied to predict subway tunnel settlement in the Sanyao Section of the Xi'an Exhibition Center in China. Prediction results from the GRA-WPSO-SVM prediction model were compared with those from the PSO-SVM and SVM using root mean square error (RMSE), mean relative error (MRE), and correlation coefficient as evaluation metrics. Results demonstrate that, the RMSE and MRE of GRA-WPSO-SVM are 0.0008 m and 1.9707%, which are better than those of PSO-SVM and SVM. Moreover, prediction results of the GRA-WPSO-SVM exhibit a strong correlation with the measured data of tunnels, with a correlation coefficient of 0.93. Obviously, the GRA-WPSO-SVM is effective. The proposed method provides an important evidence for the prediction of subway tunnel settlement and deformation trends.

Keywords: Subway tunnel, Multi-influencing factors, Support vector machine, Weighted particle swarm optimization

1. Introduction

As urbanization continues to accelerate and the demand for efficient urban transportation grows, subway systems have gradually become a crucial component of urban rail transit, effectively alleviating traffic congestion. However, the operation of subway systems has been a matter of significant societal concern. One of the key threats to the safe operation of subway tunnels is the occurrence of uneven settlement, which can be attributed to various factors. Thus, the settlement and deformation patterns of subway tunnels must be accurately predicted to ensure their structural and operational safety. Timely understanding of the settlement and deformation laws, as well as the dynamic characteristics of subway tunnels, is also essential. Hence, the prediction of subway tunnel settlement has important practical significance [1].

Subway tunnel settlement prediction techniques currently in use can be broadly categorized into three categories: techniques based on mathematical statistics, techniques based on physical mechanisms, and techniques based on machine learning. Physical mechanisms, represented by Peck empirical formula [2] and finite element method [3-4], are difficult to be implemented because they face difficulty acquiring physical parameters and constructing models and they have low calculation efficiency during prediction [5]. Methods based on mathematical statistics mainly include regression analysis [6], and fuzzy theory [7]. Methods of mathematical statistics require analysis on internal relations and development laws of abundant historical time series monitoring data during prediction, and they require data to conform to some mathematical statistical laws. Machine learning algorithms provide effective techniques to solve the above problems [8-9]. Support vector machine (SVM) is a prime example of modern machine learning and has been used extensively in pattern recognition, and regression prediction due to its advantages of high-efficiency and accurate prediction ability. It brings a new opportunity for scientific and accurate analysis and forecasting of settlement and deformation in subway tunnels.

Researchers have studied prediction of subway tunnel settlement by using SVM and improved algorithms. However, relevant studies have been performed in recursion prediction based on settlement displacement data, but they barely consider the effects of influencing factors on the prediction of subway tunnel settlement [10]. Moreover, SVM is quite sensitive to hyperparameters, which brings difficulties in model prediction. Therefore, developing a method for calculating the influences of different factors on subway settlement and constructing an optimal SVM prediction model are imperative. Hence, an improved SVM prediction model with comprehensive considerations to weights of influencing factors of subway tunnel settlement was constructed in this study, aiming to provide some references for prediction of subway tunnel settlement and prediction.

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2. State of the art

Extensive studies have been conducted by scholars on the prediction of subway tunnel settlement. Chen et al. [11] constructed a prediction model of subway tunnel settlement using six machine learning algorithms, including SVM, and verified their results using data of a 3.93 km tunnel. Their results showed that compared with traditional multiple linear regression methods, machine learning has considerable potentials in tunnel settlement prediction. He et al. [12] applied SVM for predicting subway tunnel settlement and compared with Gaussian process and wavelet neural network (WNN) results. They found that SVM was superior to WNN and Gaussian process in term of prediction. Ocak et al. [13] selected eight shield parameters that control surface settlement as the input indicators. The measured data were trained by an SVM algorithm, and the prediction model gained from simulation had relatively high accuracy. Studies have indicated that selecting SVM parameters was relatively difficult, and parameters were mainly determined according to artificial experiences or repeated tests.

Zhou et al. [14] used genetic algorithm (GA) to optimize the selection of parameters of SVM, and they performed experimental research using the measured data of tunnel structural settlement in Nanjing Metro Line 2 as an example. They found that the predicted values of SVM optimized by GA agreed better with the measured values. However, GA introduced more parameters during optimization, which resulted in difficulties of adjustment and being easily caught in local optimization. Hajihassani et al. [15] used particle swarm optimization (PSO) for constructing a hybrid model to predict subway tunnel surface deformation in Karaj, Iran. They found that the neural network via optimization algorithms by PSO could accurately predict three-dimensional ground movement caused by tunnel excavation. Hasanipanah et al. [16] combined PSO algorithm and artificial neural network to construct a prediction model for Metro Line 2 in Karaj, Iran, using multi-influencing factors as input parameters. They found that the neural network via optimization algorithms by PSO could acquire higher prediction accuracy. In comparison with GA, PSO has a simpler algorithm and faster convergence rate, but it can be easily caught into local optimization and has premature convergence during evolution. Jin et al. [17] discussed several key factors that influence existing tunnel settlement and proposed an empirical formula. The settlement curve gained from the new equation deduced from a case study was compared with practical monitoring records, showing good consistence. Xue et al. [18] established a prediction system by choosing buried depth, span as major influencing factors. They studied the deformation risk evaluation during tunnel construction and applied a prediction model to practical projects. The prediction results agreed well with the practical tunnel. Huang et al. [19] constructed a prediction model of surrounding rock compressional deformation in tunnels by combining SVM by choosing tunnel diameter, buried depth, rock quality index, and support rigidity as the four major influencing factors, which achieved a good prediction effect. Aswathy [20] constructed a prediction model using three-dimensional finite element software selecting important factors such as grouting pressure, working face pressure, tunnel diameter, and soil elasticity modulus. They verified the model using field data. Although these previous works have considered the effects of influencing factors on the prediction of subway tunnel settlement during modeling, research on the magnitude of the contribution of each factor to the prediction of subway tunnel settlement remains insufficient.

Obviously, the SVM model is highly sensitive to penalty and kernel parameters during subway tunnel settlement prediction. Although SVM after PSO avoids experience-based determination of parameters and repeated tests, PSO has some disadvantages, such as premature convergence and being easily caught in local optimization [21-22]. In addition, the prediction barely considers the effects of influencing factor weights. On this basis, a weighted PSO (WPSO) with considerations to weights of influencing factors was constructed to optimize the SVM prediction model. The subway tunnel settlement and deformation, as well as weights of influencing factors, were determined by grey relational analysis (GRA). On this basis, the adaptive weight was used to replace the PSO inertia weight to optimize the SVM parameters. A prediction model was constructed to achieve improved prediction results and provide guidance for the prediction of subway tunnel settlement and deformation.

The remainder of this study is organized as follows. Section 3 describes the GRA method for determining the influencing factor weights of subway tunnel and constructs the WPSO–SVM model for predicting subway tunnel settlement. A detailed test scheme of GRA – WPSO–SVM is also designed. Section 4 analyzes the validity of the GRA–WPSO–SVM model for predicting subway tunnel settlement. Section 5 summarizes the conclusions.

3. Methodology

3.1 GRA method is used to determine the weights

Here, GRA was applied to determine the weights of the influencing factors of subway tunnel settlement. The core idea is that the higher correlation coefficient between settlement volume and influencing factors indicates the stronger the correlation and the higher the weights will be, otherwise, the correlation will be weaker and the weight will be lower [23].

The grey relational coefficient is calculated as follows:

$$\varepsilon_j(t)=\frac{\min_j\min_t\left|y(t)-x_j(t)\right|+\rho\max_j\max_t\left|y(t)-x_j(t)\right|}{\left|y(t)-x_j(t)\right|+\rho\max_j\max_t\left|y(t)-x_j(t)\right|} \tag{1}$$

where $y(t)$ is the subway tunnel settlement volume, t=1,2, ..., n, $x_j(t)$ is the influencing factors, j=1,2, ..., m, and ρ is the resolution coefficient, with a range of [0, 1] and usually has a value of 0.5.

The weight coefficients of the influencing factors are

$$P_j=\varepsilon_j/\sum_{j=1}^{n}\varepsilon_j \qquad (j=1,2\cdots,n) \tag{2}$$

where P_j represents the weight of the influencing factors.

3.2 SVM and kernel function construction method

Suppose there is a training set of size n. x_i is the input vector and y_i is the output vector. A linear regression function was established, as shown as follows:

$$f(x)=w\phi(x)+b \tag{3}$$

where w is the weight vector, $\phi(x)$ is the mapping function, and b is the threshold.

To solve the optimization function, the objective function $Q(\alpha)$ was established [24].

$$\begin{cases} \max Q(\alpha)=\sum_{i=1}^{n}\alpha_i\sum_{j=1}^{n}\alpha_i\alpha_j y_i y_j K(x_i,x_j) \\ s.t.\begin{cases}\sum_{i=1}^{n}\alpha_i y_i=0 \\ 0\le\alpha_i\le C\end{cases} \quad i=1,2,\cdots,n \end{cases} \tag{4}$$

where $K(x_i,x_j)$ is kernel function, and C is penalty parameter.

Thus, the optimal solution $\alpha^*=[\alpha_1^*,\alpha_2^*,\cdots,\alpha_n^*]$ was acquired. There are usually three types of SVM kernel functions [10].

Polynomial function:

$$K(x_i,x_j)=(gx_i^T x_j+1)^d \qquad d\ge 1 \tag{5}$$

Radial basis function (RBF) function:

$$K(x_i,x_j)=\exp(-g\|x_i-x_j\|^2) \tag{6}$$

Sigmoid function:

$$K(x_i,x_j)=\tanh[gx_i^T x_j+\theta](g>0,\theta>0) \tag{7}$$

where g is the kernel functional parameter, and θ is the Sigmoid functional parameter.

Finally, the decision function was constructed, as shown as follows:

$$f(x)=\mathrm{sgn}(\sum_{i=1}^{n}\alpha_i^* y_i K(x_i,x_j)+b) \tag{8}$$

where x represents the input variable and f (x) represents the output variable.

3.3 WPSO algorithm

During SVM optimization, PSO used hyperparameter C and g as the positions of particles [25]. The core algorithm of the particle swarm as follows:

$$\begin{cases} V_{id}^{k+1}=\omega V_{id}^k+c_1r_1(pbest_{id}^k-X_{id}^k)+c_2r_2(gbest_{id}^k-X_{id}^k) \\ X_{id}^{k+1}=X_{id}^k+V_{id}^{k+1} \qquad d=1,2,\cdots n, \quad i=1,2,\cdots n \end{cases} \tag{9}$$

where V_{id} is the particle swarm velocity, k is the current number of iterations, ω is the inertia weight, r_1 and r_2 are random numbers within [0, 1], c_1 and c_2 are local learning factors and global learning factors, respectively, X_{id} is the position of particles, $pbest_{id}$ is the extremum of particle individuals, and $gbest_{id}$ is the extremum of particle swarm.

The inertia weight (ω) is an important index of search ability. If ω is relatively high, then it will cause excessive learning and thus fail to search the local optimal solution. If ω is relatively small, then it cannot search the global optimal solution. Thus, the adaptive weight was selected to replace the inertia weight.

$$w=w_{\max}-\frac{w_{\max}-w_{\min}}{1+\exp(|(f_i-f_{avg})/(f_g-f_{avg})|)} \tag{10}$$

where $w_{\max}$ is the maximum weight, $w_{\min}$ is the minimum weight, f_i is the fitness value of particle i, f_g and f_{avg} are the optimal and mean fitness of the particle swarm, respectively.

On the basis of the above analysis, a GRA-WPSO-SVM model was constructed for the prediction of subway tunnel settlement. Its working procedures are shown in Fig. 1.

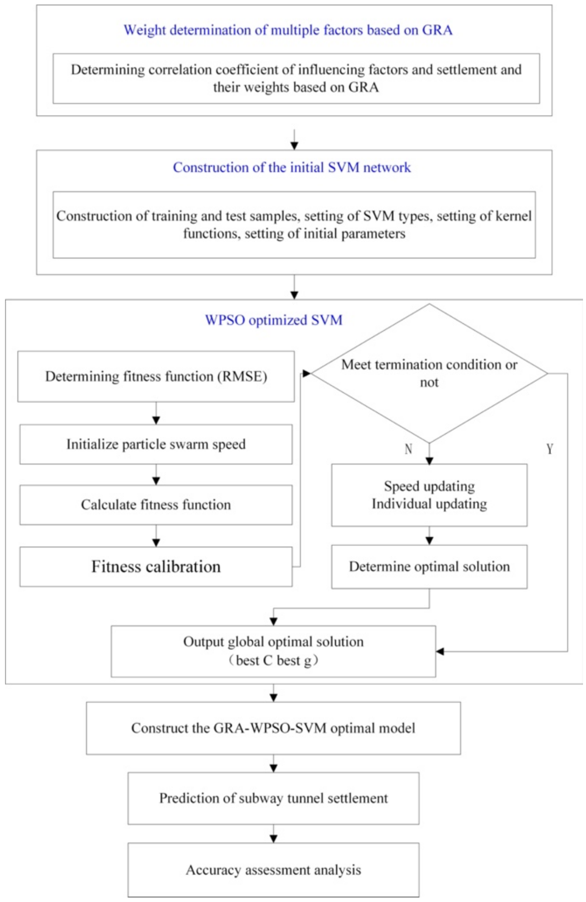

Fig. 1. Prediction process of subway tunnel settlement

4. Result analysis and discussion

4.1 Determination of influencing factor weights

Measurement data at 20 test points in the subway tunnel of Sanyao Section in the Xi'an Exhibition Center, China was selected (Fig. 2). Buried depth at different test points ranged from 7.9 m to 19.7 m, and the span was 6.88. The ranges of physical parameters were: elasticity modulus E=10~30Mpa, Poisson's ratio μ=0.35~0.45, and internal friction angle φ=15°~25° [26].

Elasticity modulus, poor geology, span, buried depth, Poisson's ratio, groundwater, and internal friction angle were selected as major influencing factors of tunnel settlement. The gray correlations between the influencing factors and settlement were calculated according to Eq. (1). The weights of the influencing factors were calculated according to Eq. (2), as listed in Table 1 and Fig.3.

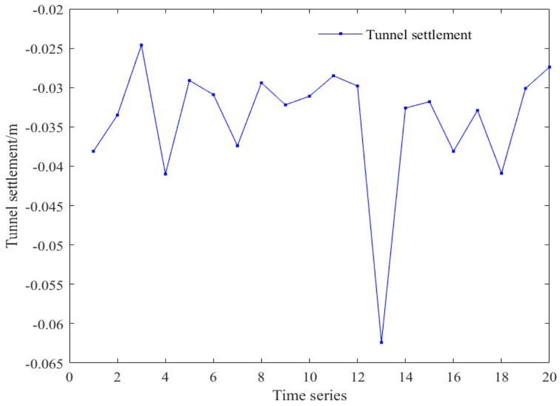

Fig. 2. The tunnel settlement curve

Table 1. Correlation and weight distribution of influencing factors

Influencing factors	correlation coefficient	weights
Elasticity modulus	0.5034	0.1296
Poor geology	0.5170	0.1331
Span	0.5143	0.1324
Buried depth	0.5081	0.1309
Poisson's ratio	0.7994	0.2059
Ground water	0.5368	0.1382
Internal friction angle	0.5044	0.1299

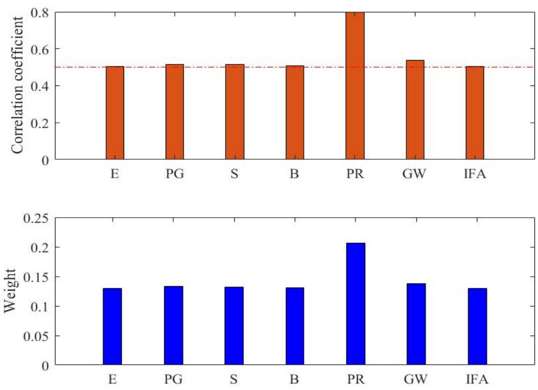

Fig. 3. Correlation and weight distribution
Note: Elasticity modulus (E), Poor geology (PG), Span (S) Buried depth (B), Poisson's ratio (Pr), Ground Water (GW), Internal friction angle (IFA)

As shown in Table 1 and Fig. 3, the order of importance for the influencing factors is as follows:
Poisson's ratio>Groundwater>Poor geology>Span>Buried depth>Internal friction angle>Elasticity modulus.
Generally, influencing factors with a correlation coefficient of≥0.5 are correlated with settlement. Influencing factors with 0.6≤correlation coefficient≤0.8 are highly correlated. The importance of influencing factors gained from the GRA agrees well with the practical situation [26].

4.2 Optimization of hyperparameters under different kernel functions

C and g are two key hyperparameters of SVM, and they influence the generalization ability of prediction models.

The SVM hyperparameters were optimized by WPSO under three kernel functions of polynomial, RBF, and Sigmoid,. Specifically, 1-15 were used to train the network, whereas 16-20 were used as the test set. The model input was: weighted influencing factors and the output was settlement. The value of the loss function was 0.01, the maximum number of iterations was 200, and the particle swarm size was 20. The local learning factor c_1 was initially 1.5, and the global learning factor c_2 was initially 1.7. The penalty factor range was (10^{-1}, 10^{2}). The kernel functional parameter range was (10^{-2}, 10^{3}). The SVM fitness curve was optimized by WPSO under different kernel functions, as shown in Figs. 4-6.

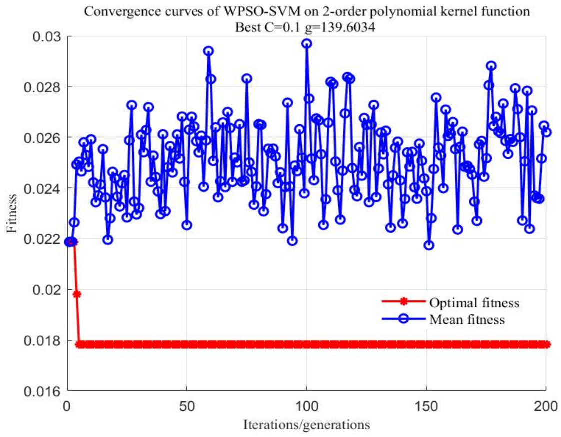

Fig. 4. Hyperparameters optimization of two-order polynomial kernel function

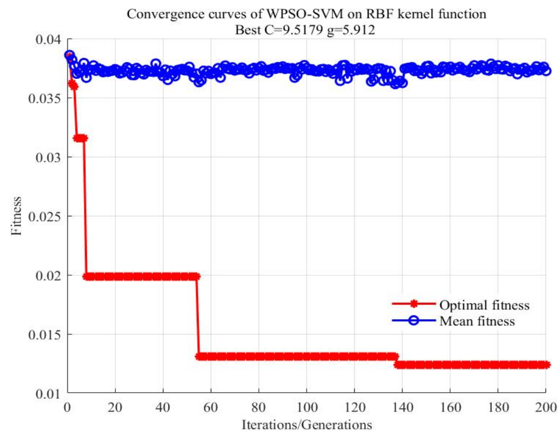

Fig. 5. Hyperparameters optimization under RBF kernel function

As shown in Figs. 4-6, the value of C determines the penalty degree to samples exceeding the error. g primarily impacts the dispersion level of the sample data in a characteristic space with multiple dimensions, consequently impacting both the range of confidence and potential risks associated with its structure.

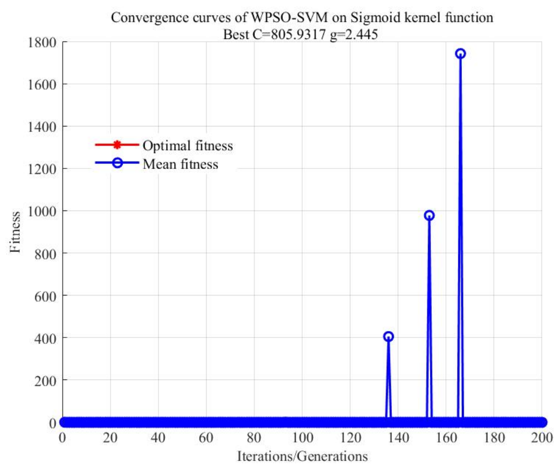

Fig. 6. Hyperparameters optimization under Sigmoid kernel function

4.3 Effect of kernel function on prediction results

To analyze the influences of different kernel functional types on the prediction results, polynomial, RBF, and Sigmoid kernel functions were applied under the same modeling sample conditions. Moreover, test samples were assessed by root mean square error (RMSE) and mean relative error (MRE), as shown in Table 2. The prediction effects of the two-order polynomial kernel function were the most ideal, and it was applied as the kernel function in the subsequent prediction.

Table 2. Effect of kernel function on prediction results

Assessment method	Linear	Two-order polynomial	RBF	Sigmoid
RMSE/m	0.0019	0.0008	0.0012	0.0018
MRE (%)	5.4357	1.9707	3.6181	4.0582

4.4 Comparative analysis of different prediction models

The GRA-WPSO-SVM was compared with SVM and PSO-SVM. In the calculation process, Samples 1-15 were selected for model training, and Samples 16-20 were chosen for settlement and deformation prediction. The prediction results and accuracy evaluation results are listed in Table 3 and Table 4, respectively. SVM, PSO-SVM, and GRA-WPSO-SVM models and their prediction effects are shown in Fig. 7.

Table 3. Comparison of the three models' prediction effects/m

Time series	Tunnel settlement	SVM	PSO-SVM	GRA-WPSO-SVM
1	-0.0381	-0.0358	-0.0372	-0.0381
2	-0.0335	-0.0355	-0.0343	-0.0335
3	-0.0246	-0.0288	-0.0237	-0.0246
4	-0.0410	-0.0351	-0.0401	-0.0410
5	-0.0291	-0.031	-0.0305	-0.0291
6	-0.0309	-0.0322	-0.0320	-0.0312
7	-0.0374	-0.0355	-0.0365	-0.0374
8	-0.0294	-0.032	-0.0303	-0.0294
9	-0.0322	-0.0336	-0.0316	-0.0322
10	-0.0311	-0.033	-0.0302	-0.0311
11	-0.0285	-0.0304	-0.0286	-0.0285
12	-0.0298	-0.0309	-0.0289	-0.0298
13	-0.0624	-0.0393	-0.0463	-0.0497
14	-0.0326	-0.0339	-0.0335	-0.0326
15	-0.0318	-0.0333	-0.0327	-0.0318
16	-0.0381	-0.0339	-0.0351	-0.0378
17	-0.0329	-0.0340	-0.0314	-0.0342
18	-0.0409	-0.0343	-0.0373	-0.0410
19	-0.0301	-0.0330	-0.0324	-0.0309
20	-0.0274	-0.0325	-0.0301	-0.0269

Table 4. Accuracy assessment of different prediction methods

Accuracy assessment methods		SVM	PSO-SVM	GRA-WPSO-SVM
Training samples	Correlation coefficient	0.7740	0.8747	0.9368
	RMSE/m	0.0065	0.0042	0.0033
	MRE (%)	8.9867	4.2146	1.4706
Test samples	Correlation coefficient	0.8114	0.9054	0.9798
	RMSE/m	0.0044	0.0027	0.0008
	MRE (%)	11.7383	7.7097	1.9707

As shown in Table 3 and Table 4, with respect to the correlation between the prediction results and monitoring values, the correlation coefficient in the GRA-WPSO-SVM model was higher than 0.9368 for the training and test samples. The correlation coefficient in the PSO-SVM was significantly better than that of the SVM. The RMSE and MRE of the GRA-WPSO-SVM are better than those of the PSO-SVM and SVM models. In sum, the GRA-WPSO-SVM model has good modeling and extrapolation abilities for the following reasons.

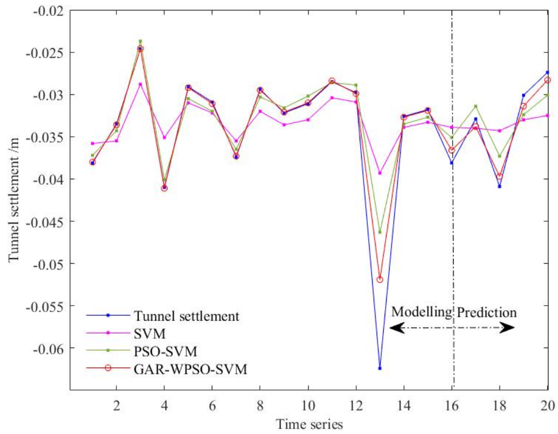

Fig. 7. Prediction comparison of the three models

(1) The SVM after PSO avoids blindness and randomness in hyperparameter selection and improves the accuracy of prediction.

(2) On the one hand, the GRA-WPSO-SVM considers the weights of the influencing factors, making the model input more reasonable. On the other hand, WPSO is used to optimize SVM, and the adaptive weight is used to replace the inertia weight, which determines model parameters more accurately. The GRA-WPSO-SVM has better prediction effect.

The prediction effects of subway tunnel settlement at deformation fluctuation points can also be used to measure model quality. As shown in Fig. 7 , in the case study, Samples 3, 4, 7, 13, and 18 could all be viewed as the points with great fluctuation changes. The fluctuation was the most prominent at Sample 13. The GRA-PSO-SVM model had excellent performances at the above points, which could further prove the effectiveness of the model.

5. Conclusions

To obtain high prediction accuracy of the subway tunnel, a GRA-WPSO-SVM model is proposed and compared with PSO-SVM and SVM for the prediction of subway tunnel settlement. Some major conclusions could be drawn as follows:

(1) The influencing factors of subway tunnel settlement are screened by the gray relation theory, and their sequence of importance is determined. On this basis, weights of different influencing factors are determined, and the prediction accuracy is improved.

(2) During SVM modeling, the selection of kernel function supplement, penalty factors, and kernel functional parameters can influence the prediction results greatly. The WPSO algorithm replaces the PSO inertia weight by the adaptive weight, optimizes the SVM to avoid the complicated trial process of parameter optimization. As a result, the prediction results are more stable.

(3) The proposed GRA-WPSO-SVM model not only considers the weights of the influencing factors reasonably but also optimizes SVM parameters by WPSO. The

prediction results agree well with the practical monitoring value. It can increase analysis efficiency on future subway tunnel settlement and deformation.

In this study, the GRA and WPSO-SVM are combined to investigate the effects of influencing factors on the prediction of subway tunnel settlement thoroughly. The GRA-WPSO-SVM model is constructed successfully. The influencing factors of subway tunnel settlement are mainly chosen based on previous experience. A more comprehensive test of influencing factor could be designed to further optimize the prediction of subway tunnel.

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