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Research Article

Monitoring and Prediction of Highway Foundation Settlement Based on Particle Swarm Optimization and Support Vector Machine

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Highway construction has always been an important strategy in China's construction projects. However, because the soil in the construction area belongs to the soft soil zone, there will often be large vertical deformation in the construction process, which will seriously affect the engineering quality, so the highway FS (foundation settlement) prediction is particularly important. In order to improve the accuracy of highway stability prediction and ensure the safety of highway engineering, a prediction model based on PSO_SVM (support vector machine for particle swarm optimization) is proposed. By using the particle velocity and its position in the PSO algorithm to correspond to the kernel function parameters and penalty factors of the parameters in the model, the optimal parameters are found and substituted into the SVM prediction model to obtain the PSO_SVM. The results show that the MAD of section A# and section B # of PSO_SVM is 0.8991 and 1.3027 for different monitoring points. *Conclusion*. PSO_SVM has a strong learning and generalization ability, high prediction accuracy, stability, and adaptability, and can reflect the overall change information of highway FS data, which has practical application value.

1. Introduction

In the process of subgrade excavation of the project, excavators and bulldozers are used together, and the construction is carried out in different layers. In case of any change in the geological conditions of the soil layer during the construction, it shall be reported to the supervising engineer in time to facilitate the timely adjustment of the slope ratio. During mechanical excavation, attention shall be paid to the protection of underground pipelines, cables, and other structures. When the excavation is close to the slope, the construction contractor shall stop using manual excavation to properly excavate and trim the slope. Where the subgrade and slope are connected, earthwork shall be reserved in advance, which is conducive to the stability of the slope in the later stage. In the process of mechanical excavation, the design requirements shall be strictly followed to ensure that the excavation depth meets the design requirements and avoid over excavation. In addition, backfill materials shall be used in a timely manner for backfilling and compaction to ensure that the subgrade bearing capacity meets the requirements. With the increase of expressway construction scale, the problem of soft soil is becoming more and more serious, which has become one of the important factors affecting the stability of highway opening in operation period [1]. In the process of expressway construction with soft soil subgrade, in order to ensure the construction quality of expressway subgrade, the stability of pavement during the postconstruction operation period, and the safety of vehicles, it is necessary to predict the final settlement of soft soil subgrade, so as to provide reference for determining the subgrade filling scheme. In a period after construction, monitoring and data prediction of soft soil FS (foundation settlement) can improve the stability and bearing capacity of this section of highway subgrade, so as to reduce the occurrence of accidents.

Wang et al. [2] apply the numerical method to FS prediction; Li et al. [3] apply grey theory to FS prediction; Li et al. [4, 5] put forward several methods to calculate the settlement of sand drain foundation. The results show that the settlement of sand drain foundation caused by lateral deformation must be paid attention to. In reference [6], the grey theory is used to predict FS in unequal distance, and the corresponding GM (1, 1) model is established. Kim et al. [7] propose to optimize the parabolic settlement prediction model by using real code accelerated genetic algorithm. Zhou et al. [8] put forward a method to predict FS by using the momentum BP algorithm. Hu et al. [9] used the traditional three-layer BP network model to study this problem, and achieved satisfactory results. Liu et al. [10] apply wavelet time series model to subway settlement prediction, and prove that this model has the characteristics of gross error detection and robust interference. Chen [11] combines wavelet denoising and grey-time series model to predict the surface of subway lines, and good prediction results have been achieved.

With the passage of time, the ground buildings will have different degrees of settlement and deformation. At present, the numerical simulation method, the grey prediction model, and the artificial neural network for predicting the surface subsidence and deformation have their own defects. SVM (support vector machine) has good mathematical properties and shows good generalization ability, but its performance depends on the parameters of the learning algorithm. However, there is no fixed method for selecting SVM parameters, which can only be selected through experimental comparison. Therefore, the parameter determination of SVM has always been a hot issue in research [12, 13]. Therefore, a highway FS prediction method based on PSO_SVM (SVM based on particle swarm optimization) is proposed. Among them, PSO is used to select the optimal combination of SVM training parameters. According to the optimized SVM parameters, a vector machine model is established. Finally, the performance of the model is evaluated, and good results are achieved.

2. Research Method

2.1. On-Site FS Monitoring of Highway. The landform, geological conditions, and hydrological conditions along the roads in mountainous areas are complex and uncertain. The subgrade is filled and excavated frequently, and there are many deep excavation and high filling sections, which make the physical and mechanical properties of the subgrade very different and cause uneven settlement of subgrade and instability. This requires in-depth study of engineering geological conditions to find more targeted survey methods and means. Complete and accurate engineering geological data for the design and construction of mountain highways were provided. Therefore, it is necessary to fully understand the engineering geological conditions of the area before building mountain roads. Whether the roadbed can run stably for a long time is closely related to the geological structure. Highway construction is largely influenced by the strength of soil permeability, soil stress of foundation soil layer, change of groundwater level, and soil thickness. In addition, climatic conditions are also an important factor leading to subgrade settlement. In the process of highway subgrade filling construction, in order to speed up the construction progress, the on-site constructors did not carefully observe the highway subgrade and filling height, and did not fully consider the FS problem, which caused the foundation capacity to fail to meet the standard requirements, resulting in FS and cracks.

The stable observation of soft soil foundation settlement during construction and operation is an important link in highway construction. In the process of embankment filling, the load acting on the pressed rubble composite subgrade will gradually increase, which will lead to consolidation settlement of the composite subgrade. For this kind of situation, we can use the method of burying section pipes on the surface of composite subgrade or the bottom of embankment along the cross section and using inclinometer to test the section settlement deformation of composite subgrade during embankment filling, so as to deal with the settlement problem by controlling the load.

During the widening construction of expressway subgrade, the original load on the old subgrade was changed, resulting in the second settlement deformation of the old subgrade. At the same time, the settlement of newly built subgrade before the end of construction is called the first settlement only under the action of its own weight; the settlement of newly built subgrade is called the second settlement [14].

Due to the difference of physical properties and construction technology of different fills, it is not yet possible to form a unified result. At present, the research on differential settlement of widening subgrade usually adopts the back analysis method, that is, the data obtained by settlement monitoring are analyzed, the empirical formula is obtained, and then the change law of FS with time is inferred, and the calculation formula of main consolidation settlement is determined by analysis, such as the following formula:

$$S_c = \sum_{i=n}^{n} \frac{e_{0i} - e_{1i}}{1 + e_{0i}} \Delta h_i, \tag{1}$$

where n is the number of layers calculated by FS; Δh_i is the thickness of the i-th layer after subgrade stratification, generally 0.5~1.0 m; e_{0i} is the relevant void ratio between subgrade stratification and the dead weight stability of the i-layer subgrade soil; and e_{1i} is the relevant void ratio between subgrade stratification and i-layer subgrade soil after additional load and dead weight stability.

When carrying out road subgrade filling, the filling speed should be strictly controlled, and the measured value of surface settlement should be taken as a reference to accurately judge the FS trend, so as to have a clear understanding of the objects and time range required for preloading and unloading, and thus have an accurate grasp of the construction time of the pavement [15, 16]. According to the measured data, the surface uplift state is analyzed. Finally, the underground horizontal displacement meter should be used to measure the underground soil layers, so as to obtain the specific displacement, and through the obtained displacement, the damaged position of the soil can be analyzed, so as to ensure that the subgrade will not settle.

For sections with poor geological conditions, the method of improving soil quality can be selected. Construction workers generally choose drainage consolidation method, which can effectively improve the soil hardness of subgrade.

2.2. Overview of PSO and SVM

2.2.1. PSO Principle. The basic principle of PSO is as follows: Assuming that there are n particles flying at a constant speed in D-dimensional space, population $X = (X_1, X_2, \cdots, X_n)$, and then $X_i = (x_{i1}, x_{i2}, \cdots, x_{iD})$ is the position of the i-th particle and $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$ is the velocity of the i-th particle.

According to the number of target pictures, the fitness value corresponding to X_i is calculated, $P_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$ is its individual extreme value, and $P_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$ is the global extreme value of the population.

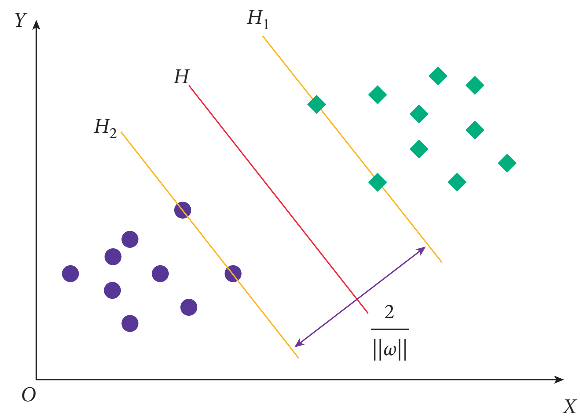

Figure 1: Optimal hyperplane.

The updated formula of the velocity and position of the particle is as follows:

$$\begin{aligned} v_{ij}(t+1) &= wv_{ij}(t) + c_1 r_1\left(p_{ij}(t) - x_{ij}(t)\right) + c_2 r_2\left(p_{gi}(t) - x_{ij}(t)\right), \\ x_{ij}(t+1) &= x_{ij}(t) + v_{ij}(t+1), \end{aligned} \tag{2}$$

where w is the inertia weight, $i = 1, 2, \cdots, n$; $j = 1, 2, \cdots, d$.

2.2.2. SVM Principle. SVM is a new general learning method developed on the basis of statistical learning theory. It is based on the principle of structural risk minimization, and has strong learning ability and generalization ability. It can solve the problems of small sample, nonlinearity, local minima, etc., so as to make effective classification.

Main idea of SVM: this theory adopts the structural risk minimization criterion, maps the input vector to a high-dimensional feature space through preselected nonlinear mapping, and constructs the optimal decision function in this space [17].

Assume a training sample set $(x_i, y_i)_i^N$, in which the input data $x_i \in R^n$ and the output data $y \in R$ construct the optimal linear function in the high-dimensional feature space:

$$f(x) = w^T \varphi(x) + b, \tag{3}$$

where w is the weight and b is the bias term.

The optimal classification surface can not only correctly separate the two types of training samples, but also requires the maximum classification interval (Figure 1).

Support vector machine has been widely used in pattern recognition, regression estimation, probability density estimation, and other neighborhoods. However, the emergence of support vector machines has promoted the rapid development of kernel-based learning methods, which enable researchers to efficiently analyze nonlinear relationships. This high efficiency can only be obtained by the linear algorithm.

Support vectors are sparse, which only accounts for a small part of the training samples. This feature is of great significance for solving large-scale problems. The performance of SVM mainly depends on the model selection. Different kernel functions and parameters can be selected to construct different SVM, and the results and generalization ability are also different [18].

Polynomial kernel function:

$$K(x, y) = (x \cdot y + 1)^d. \tag{4}$$

For a given training sample, the dimension of the system depends on the degree d of the polynomial, so we can control the dimension of the system by choosing the appropriate value d.

Sigmoid kernel function:

$$K(x, y) = \tanh(v(x, y) + a). \tag{5}$$

The S-shaped function adopts the hyperbolic tangent function tanh, which can satisfy the Mercer condition if and only if v, a takes an appropriate value.

Kernel determines the generalization ability of SVM. The essence of SVM is to transform linear inseparable variables into linear separable variables by selecting kernel functions, and then calculating them [19–22]. In the above process, the selection of kernel parameters will also have a great influence. Therefore, we must pay attention to the selection of kernel function and related parameters.

2.3. Establishment of PSO_SVM for Highway Monitoring and Prediction of FS

FS is one of the main monitoring contents. Because of the complex nature of soft soil, there are too many assumptions in the research of settlement theory, and the selection of various parameters will also be different from the original soil layer, which is inconsistent with the graded sand loading of road foundation treatment in the process of reclamation, and the accuracy of settlement calculation is not enough, so it is difficult to be widely used in engineering. Engineering experience shows that this method is accurate and reliable, and the form and development trend of curve meet the law of FS quantity development with time.

Under the influence of external load, excess pore water pressure is formed in saturated soil. In this case, the theory can be used for calculation. However, in practice, with the change of time and depth, the consolidation coefficient of soft soil with nonlinear characteristics and high compressibility will change greatly. Obviously, this theory is not applicable to solve it.

Soft soil has the characteristics of high compression, low strength, low permeability, etc. The engineering geological conditions along this high-grade highway change greatly, and the basic characteristics of the foundation are difficult to accurately grasp due to the disturbance of the soil caused by the construction. The deformation is mainly caused by normal stress, which will only make the volume of soil shrink and compact, and will not lead to soil destruction. At this time, the air content in the soil is very small, so the proportion of its compression in the total compression of the soil is not large. Except in some cases, it is necessary to consider the compression of closed gas, which can generally be ignored.

Because of the difference of embankment height and uneven settlement of foundation, uneven deformation of pavement occurs. Uneven settlement of subgrade exceeds a certain limit, which will lead to the functional and structural damage of pavement, and make the highway unable to meet the design requirements. With the increase of filling height, load, and time, the pore water in foundation soil is gradually discharged, the excess pore water pressure is gradually dissipated, and the soil is gradually compacted to produce volume compression deformation, and it enters the elastic-plastic state. At this time, the settlement rate of soil increases rapidly.

According to the statistical theory, SVM determines the regression function by minimizing the following target numbers:

$$\min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}\left(\xi_i + \xi_i^*\right),$$
$$s.t. \begin{cases} y_i - w\phi(x) - b \leq \varepsilon + \xi_i, \\ w\phi(x) + b - y_i \leq \varepsilon + \xi_i^*, \\ \xi_i, \xi_i^* \geq 0, \end{cases} \tag{6}$$

where ξ_i, ξ_i^* is a non-negative relaxation variable; C is a penalty factor, which is a compromise between empirical risk and model complexity; ε is an insensitive loss function parameter.

Due to the uneven distribution of the initial population, the PSO algorithm is prone to premature phenomenon in the learning process. In order to avoid this shortcoming, chaotic particle swarm optimization based on logistic equation can be used. When the particle falls into the local optimum, the chaotic disturbance is used to jump out of the local optimum. Therefore, the "subjective initiative" of particles is introduced to improve the "passive learning" characteristics of standard PSO, and the "active detection" step of particles is added.

Using the LODISTIC chaotic sequence equation, $T +$ 100 random positions are formed in D-dimensional space. The formula is as follows:

$$\begin{gathered} c(t+1, d) = a(d) \times c(t, d) \times (1 - c(t, d)), \\ a(d) = 3.6 + 0.2 \times rand, \\ x(t, d) = l(d) \times c(t + 100, d), \end{gathered} \tag{7}$$

where t is the current iteration time, $l(d)$ is the length of the d dimension, and *rand* is a random number in [0, 1], $d = 1, 2, \cdots, D$.

Then, the Lagrange method is used to solve the dual optimization problem:

$$L = \frac{1}{2}\omega \times \omega + C\sum_{i=1}^{n}\left(\xi^i + \xi_i^*\right) - \sum_{i=1}^{n}\alpha_i\left[\xi^i + \varepsilon - y_i + f(x_i)\right] - \sum_{i=1}^{n}\alpha_i^*\left[\xi_i^* + \varepsilon - y_i + f(x_i)\right] - \sum_{i=1}^{n}\left(\xi_i\gamma_i + \xi_i^*\gamma_i^*\right), \tag{8}$$

in which $\alpha_i, \alpha_i^*, \gamma_i, \gamma_i^* \geq 0$ is Lagrange multiplier and ε is allowable error. L to minimize $\omega, b, \xi_i, \xi_i^*$ is to find the maximum ${}^{i}_{\alpha}, \alpha_i^*, \gamma_i, \gamma_i^* \geq 0$.

The fitness function of each particle is:

$$S(x) = \left(\sum_{i=1}^{N}\frac{y - y_i}{N}\right)^{1/2}, \tag{9}$$

where y_i represents the measured value of the i-th sample; y is the predicted value of the i-th sample; and $i = 1, 2, \cdots, N$ (N is the number of test samples) to calculate the fitness value of each particle.

For each particle, the optimal position of the individual is compared with the optimal position of the group, and if it is compared, it is replaced by the optimal position of the group; otherwise, the optimal position of the group is unchanged.

The estimated $\widehat{f}$ depends on two variables α, β, namely, $\widehat{f} = \widehat{f}(\alpha, \beta)$, where β is the structural parameter and α is other parameter that affects the performance.

Assuming that the training set $\{X, Y\}$ is divided into training set $\{X_t, Y_t\}$ and confirmation set $\{X_v, Y_v\}$, the errors of training and confirmation are defined as formula (7) and formula (8), respectively:

$$R_{train}(f) = \frac{1}{m_{\text{train}}} \sum_{x_i, y_i \in \{x_t, y_t\}} e(x_i, y_i, f(x_i, y_i)),$$
$$R_{\text{valid}}(f) = \frac{1}{m_{\text{valid}}} \sum_{x_i, y_i \in \{x_v, y_v\}} e(x_i, y_i, f(x_i, y_i)). \quad (10)$$

In the above formula, $e(\cdot)$ is the loss function.

Appropriate kernel function parameter g and penalty factor C are the keys to improve generalization ability and classification performance of SVM algorithm. However, PSO has few parameters and is easy to implement.

Therefore, searching for the best g, C through PSO can improve the accuracy of SVM prediction results. The flow of highway stability analysis based on PSO_SVM is shown in Figure 2.

3. Result Analysis

For highway construction projects, soft soil foundation treatment technology is an indispensable part. Soft soil foundation treatment technology not only occupies a very important position in the whole highway engineering construction but its construction quality has a great impact on the final quality of highway construction projects in China. Therefore, it is necessary to avoid the highway engineering construction project quality failing to meet the relevant standards caused by the soft soil foundation treatment technology to a great extent. In order to ensure the safety of people's travel to a certain extent, relevant personnel need to increase the research on soft soil foundation treatment technology in highway engineering construction. In this case, the settlement of expressway is mainly caused by the high load of soft soil subgrade. The soil used to fill the paving foundation has certain compressibility, and under the action of high load, the volume of the roadbed will be reduced, consolidated, and deformed, and then settlement will be formed. In spatial distribution, soft soil has the characteristics of discontinuity and large thickness difference. These characteristics of the soft soil layer determine that the secondary consolidation settlement of the soft foundation section of the expressway is relatively large, and the settlement difference of some sections is obvious, which is directly reflected in the large postconstruction settlement of some sections.

The soft soil in the soft foundation section of the expressway is composed of dark grey or black flowing plastic silt or peat soil, which contains a large amount of humus such as plant roots and stems. Besides the commonness of conventional soft soil, the expressway in the case also has the characteristics of high organic matter. In this chapter, the section settlement data of a highway in a case is used, and a comprehensive analysis is carried out according to the section detection and settlement indicators in the data.

The PSO_SVM is used to predict the FS quantity, which has no strict requirements for the measured data. Three sections (A#, B#, C#) are selected, and the settlement data of these sections are obtained. Based on the PSO_SVM, the prediction method is to write the corresponding program in MATLAB. After obtaining the settlement data of each section, the corresponding improved SVM model can be established, as shown in Figure 3, which shows the related results of settlement prediction curve.

As shown in Figure 3(c), the predicted values in the settlement prediction of three sections of pso\u SVM are almost the same as the actual values. Group C was the most stable. PSO_SVM, PSO, and SVM are used to make mathematical statistics on C# section data, and the required parameters are obtained by fitting. According to the corresponding model, the corresponding parameters are adopted to predict the subsequent settlement. The simulation of the three forecasting methods is shown in Figure 4.

It can be seen that the PSO_SVM is basically consistent with the measured values. Among them, the prediction error of PSO_SVM ranges from 0.2 cm to 1.6 cm. It is not difficult to see that the error of SVM is the largest, the error of PSO is slightly smaller, and the error of PSO_SVM is the smallest. PSO_SVM can simulate the settlement value more accurately, with the smallest error among various models, and can better meet the requirements of engineering accuracy.

The settlement expressions fitted by the above three models are used to predict the settlement of section A# after 60 days, as shown in Table 1.

Obviously, the biggest deviation is PSO, followed by SVM, and the predicted value of SVM is smaller than the measured settlement, which is quite harmful to the actual project. It is impossible to predict whether the settlement is too fast, and PSO_SVM can predict the settlement in the short term.

PSO_SVM can determine the undetermined parameters according to the observed samples, so as to more accurately predict and reflect the postconstruction settlement law of soft soil foundation. PSO_SVM can conveniently predict the postconstruction settlement at any time according to the existing field measured data, so as to judge whether the subgrade deformation is stable or not, and provide decision-making basis for the paving of permanent pavement and the maintenance of pavement.

In order to compare the accuracy between models, the prediction data error of each model and the overall prediction accuracy of the model are summarized together. In this article, MSE (mean square error), RSS (residual sum of squares), and MAD (mean absolute deviation) will be used to evaluate the prediction accuracy of each model one by one. The comparison and summary results of the prediction accuracy of each model of section A# and B# are shown in Figures 5 and 6 and Table 2, respectively.

It can be seen that for different monitoring points, the prediction accuracy of PSO_SVM is higher than that of the traditional SVM model and the PSO model, which shows that PSO_SVM has strong adaptability. The MAD of section A# and section B # of PSO_SVM is 0.8991 and 1.3027, which proves that PSO_SVM has high prediction accuracy and stability. Compared with the other two models, it has a great advantage in prediction accuracy, all indexes are better than the other two models, and the stability of the model is better.

In practice, a particle is often affected by many factors, and all these factors appear in an optimal form, so what

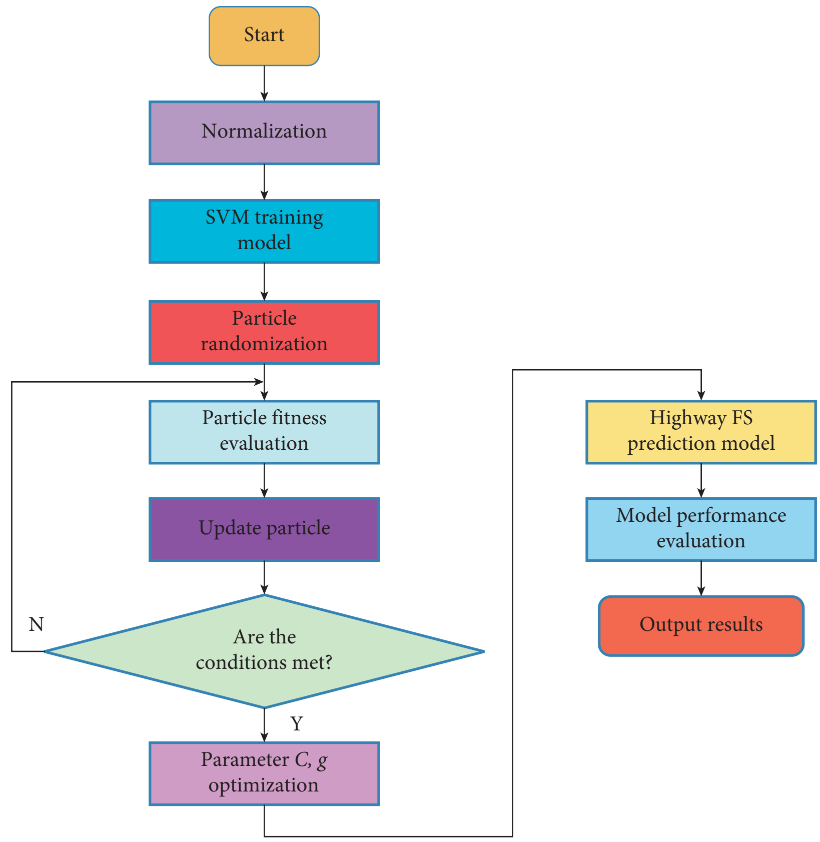

Figure 2: PSO_SVM highway FS prediction process.

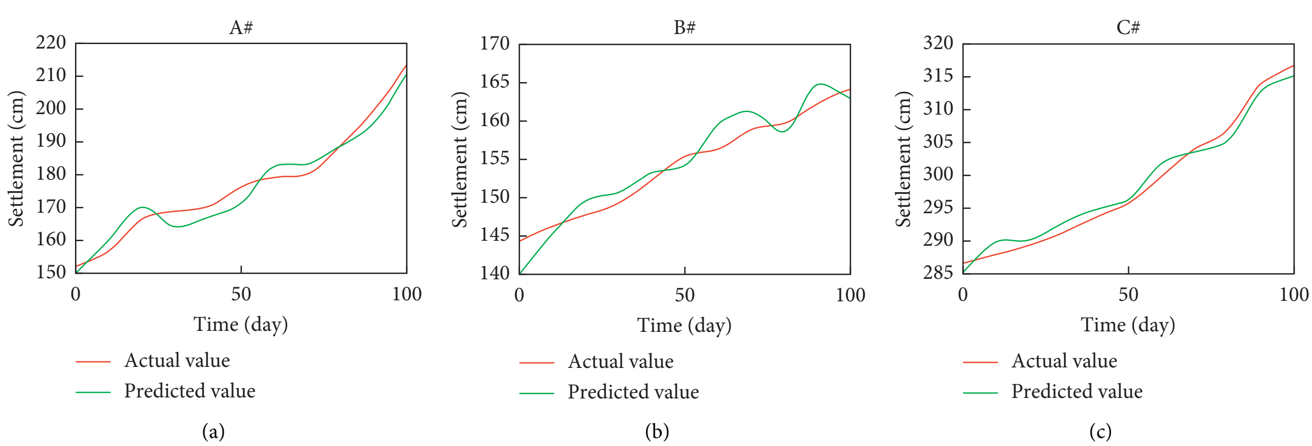

Figure 3: Settlement prediction of three sections by PSO_SVM.

happens is that the predicted value of the particle is less than the actual value. Otherwise, it is greater than the actual value. However, this kind of situation is generally difficult to achieve, and the usual situation is that some factors are in a good state, some are in a bad state, and most of them are in a medium state, so the predicted value is in good agreement with the actual value.

In a word, PSO_SVM has strong learning and generalization ability, high prediction accuracy, stability and adaptability, and can well reflect the overall change

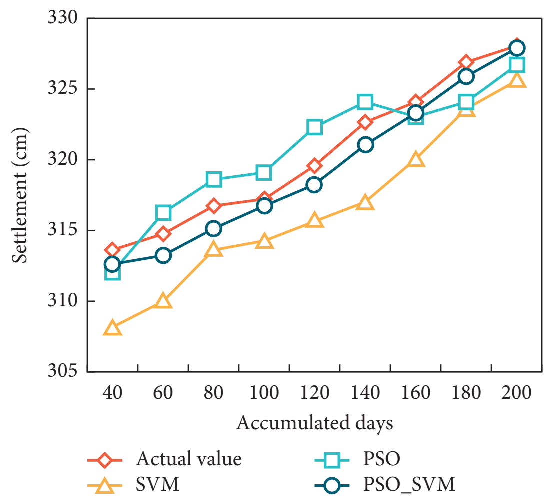

Figure 4: C# section settlement prediction analysis.

Table 1: Comparison of measured settlement values of section A# with predicted settlement values of different models.

Cumulative days	Measured settlement	SVM	PSO	PSO_SVM
260	346.8	340.1	343.8	344.9

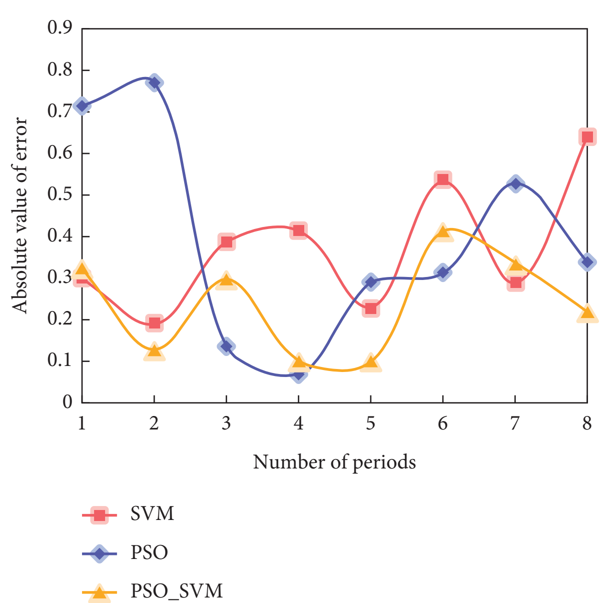

Figure 5: Error of prediction data of various models in section A#.

Table 2: Accuracy evaluation index of each model.

Section	Prediction model	MSE	RSS	MAD
A#	SVM	0.1227	0.8619	3.3284
	PSO	0.0812	0.5512	2.7146
	PSO_SVM	0.0123	0.0864	0.8991
B#	SVM	0.0714	0.4428	1.9681
	PSO	0.2886	1.7416	3.6687
	PSO_SVM	0.0311	0.1893	1.3027

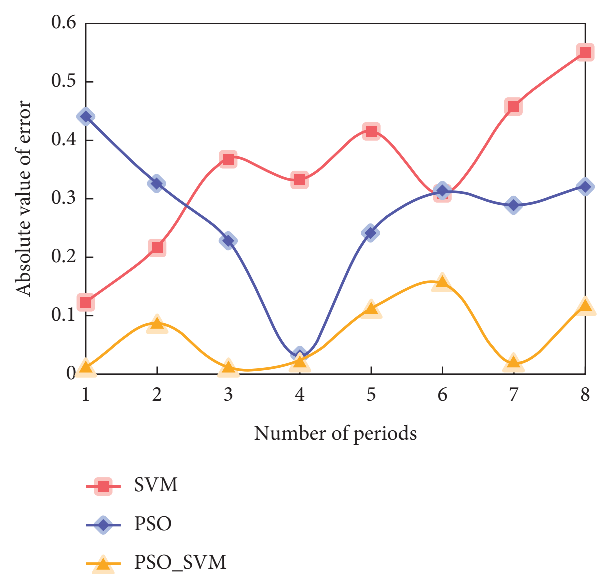

Figure 6: Error of prediction data of each model in section B#.

information of highway FS data, which has certain research significance and popularization value in practical engineering.

4. Conclusion

FS prediction of soft soil is a nonlinear and high-dimensional data processing problem, and SVM can solve this kind of data prediction problem well. Therefore, it is necessary to study the appropriate settlement prediction method for the settlement of soft soil subgrade, so as to guide the actual construction, make the settlement within the predictable range, and ensure that the difference between the predicted value and the measured value is small. It is our goal to improve the existing FS calculation and prediction methods, so that the predicted value of settlement is closer to the measured value. This article discusses the use of PSO algorithm to optimize the selection of three parameters of

SVM, namely, insensitive loss coefficient, penalty coefficient, and kernel parameter. Through specific tests, the results show that PSO_SVM is obviously superior to the other two models in prediction accuracy for different monitoring points, and the deformation data can better reflect the overall change information of highway FS data, which has certain popularization significance in practical engineering. However, how to accurately predict their settlement will be an important issue in highway construction. Therefore, the research of this article needs to further analyze and elaborate on this point.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interests.

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