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Research Article

Machine-Learning-Based Road Soft Soil Foundation Treatment and Settlement Prediction Method

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In order to effectively predict the settlement of soft soil foundation, improve the accuracy of road soft soil foundation settlement prediction, and improve the safety of the project, this paper proposes an optimized SVM-AR model and discusses the application scope of the SVM model and the time series AR model, respectively. The SVM-AR model is proposed by combining the respective advantages of the two types of models. Firstly, the prediction method of foundation settlement is analyzed and studied, and then the improved ABC algorithm is used to optimize the SVM model. Secondly, the optimized SVM model is combined with the AR model, the ABC-SVM model is used to predict the trend settlement, and the AR model is used to predict the random settlement and then combined to obtain the predicted settlement. The example verification shows that SVM-AR is more accurate than the SVM model prediction results and better reflects the settlement process of highway soft soil foundation.

1. Introduction

With the rapid development of my country's economy, a large number of rural population poured into cities, resulting in an increasing shortage of urban land. More and more civil and industrial high-rise buildings have attracted more and more attention, and the safety of high-rise buildings and some buildings with special requirements has become an urgent problem to be solved [1, 2]. My country has a vast territory and diverse geological and geomorphological conditions. In recent years, the construction of some airports, granaries, oil storage tanks, and large steel plants has shifted to soft soil areas with special geological environments. The most important thing to build structures in these soft soil areas is to solve the problems of foundation settlement and stability of structures. With the development and utilization of soft soil areas by government departments, the problem of foundation settlement of buildings in soft soil areas not only affects the project cost and project cycle, but also affects the quality of the entire project [3–6].

The most important mechanical properties of the soil after repeated loads are the strength of the soil and the deformation of the soil. The influence of the settlement of the foundation on the upper buildings can be accurately determined according to the deformation of the soil under the action of long-term cyclic loads. It is one of the main research topics in the field of civil engineering [7]. For the structures built on the soft soil foundation, the corresponding foundation treatment has been carried out before construction, such as overload preloading, cement mixing piles, compacted sandstone piles [8]. However, there are few studies on the settlement of the foundation under the action of repeated loads (the rise and fall of the oil level in the oil tank, the load change caused by the loading and unloading of grain in the granary) for the building above the foundation. Therefore, the prediction of soft soil foundation settlement is still very important in practical engineering practice [9–11].

Due to the differences in geological survey, simulation test, and manual calculation methods, the expected situation during design is often different from the actual foundation treatment and subgrade construction progress, and there is generally a large error in the actual subgrade settlement and its change process from the initial design stage [12–15]. Therefore, when necessary, it is necessary to accurately predict the later settlement and modify the original data through the field measured settlement data, that is, to carry out dynamic design and construction control of the settlement of soft soil subgrade during actual construction. If the settlement amount during construction or post-construction settlement is too different from the design value, it will cause the bridge head to jump and the road surface to sink. Therefore, accurately predicting the settlement of highway soft soil foundation is an important geotechnical problem. With the continuous investment in highway construction and the increase in the calculation section of soft soil subgrade, a model is needed that can easily and accurately predict settlement. To improve prediction reliability and accuracy, various settlement calculation models have been proposed. At present, the subsidence prediction methods mainly include support vector machine, hyperbolic method, grey theory method, and neuron network [5, 16–19]. The above methods have improved the accuracy of soft foundation settlement prediction to a certain extent, but at the same time there are shortcomings. The foundation settlement not only has a certain regularity, but also has a relatively high performance due to the comprehensive effect of various influences on the subgrade settlement process. Because of strong randomness, the actual process of settlement often cannot be accurately reflected when a single prediction model is used.

Therefore, this paper proposes an optimized SVM-AR combination model, uses the improved ABC algorithm to optimize the SVM, and then uses the improved SVM model and AR model to predict the trend and random quantities of building settlement deformation to reflect the foundation settlement. The characteristics of regularity and randomness make the prediction results more accurate.

2. Analysis and Research on Prediction Method of Foundation Settlement

2.1. Deformation Mechanism of Foundation Settlement. The engineering community believes that the deformation mechanism of soft soil foundation settlement can be roughly divided into three stages: instantaneous settlement S_d, primary consolidation settlement S_c, and secondary consolidation settlement S_s. The general formula for foundation settlement calculation is

$$S(t) = S_d(t) + S_c(t) + S_s(t). \tag{1}$$

Instantaneous settlement is actually the settlement value of the foundation at the moment when the building is subjected to the load transferred from the outside and has no direct impact on the discharge of pore water in the foundation soil. The main factors affecting the instantaneous settlement are the loading rate and the loading method. Due to the different loading methods at different times, the effective stress in the soil is different, and the deformation modulus of the soil is also different; the main consolidation settlement is due to the pore water flowing from the soil. The flow out of the soil will cause the volume of the soil to gradually decrease, which will eventually lead to an increase in the settlement of the soft soil foundation. The stress increases; in other words, the settlement of the foundation increases [20]. The most important part of the three parts of foundation settlement is the main consolidation settlement; in general, people think that the subconsolidation settlement is the settlement amount that begins when the super void water pressure basically disappears. It is very small, and it takes a relatively long time. This is just what people think is that the foundation settlement is divided into three stages. In fact, the three stages of foundation settlement are basically generated at the same time from the beginning of loading. Because soils with different properties have different internal complex mechanical properties, the proportions of the three types of settlement in the total settlement are also different, and the dominant time in the entire settlement process is also different [21].

2.2. Foundation Settlement Prediction Method. The prediction of foundation settlement is very important, which not only has certain guiding significance for the construction in the early stage of the project but also can play a role in predicting the foundation settlement after the building is completed and put into use. The most important method of traditional foundation settlement prediction is the layered sum method to predict the foundation settlement [22]. In the calculation process of the layered sum method, the formula is relatively simple and the relevant parameters used are not too many, and the parameters are relatively easy to obtain. However, the precondition for the prediction of foundation settlement by this method is to only consider the influence of vertical load on foundation settlement and deformation. It is assumed that there is no influence of longitudinal load on foundation settlement and deformation. Both vertical load and longitudinal load have different degrees of influence on the settlement and deformation of the foundation. The assumed preconditions of this method are quite different from the actual influencing factors of foundation settlement, which will eventually cause a large error between the predicted results of foundation settlement and the actual settlement value. The settlement and deformation are roughly described, not as a reference for the actual construction and maintenance in the later stage. One of the traditional methods for predicting foundation settlement is the numerical analysis method [23]. Combine this model and some related parameters and then get the foundation settlement value we want. However, in the actual application process, due to the relatively many related parameters involved and the vagueness of the parameter values, there is no recognized normative value. Due to the influence of various aspects such as the environment, there is also a large error between the final data and the actual foundation settlement deformation value. Therefore, the numerical analysis method to calculate the foundation settlement value is also gradually eliminated [24].

In recent years, with the development of numerical analysis methods such as finite element methods in soil mechanics, the calculation parameters involved in their models are difficult to test, and many existing numerical calculation methods are due to researchers' understanding of soil constitutive models. The description is not clear enough and the actual calculation conditions are not mature enough to make the obtained results unsatisfactory. Therefore, it is thought that the later settlement can be estimated based on the measured settlement data. The more common prediction methods are curve fitting method, grey system prediction method, Asaoka method, artificial neural network method, and some traditional settlement prediction methods.

(1) Curve fitting method (hyperbolic curve method, exponential curve method, and Poisson curve method) belongs to the prediction and analysis of the later settlement trend based on the existing experience combined with the settlement data observed in the previous period, among which there are the hyperbolic curve and logarithmic curve. In the prediction process, the model has some shortcomings and deficiencies, such as requiring the sample distribution to be studied to have specific properties, and there are many information parameters. It is also impossible to predict the foundation settlement in the later stage because the measured settlement time is relatively short.

(2) The gray system prediction method does not have very strict requirements on the measured settlement data, and the gray system prediction method itself is a dynamic prediction. In the actual prediction process, the model can be adjusted according to the newly added measured data. Adjustment: but the calculation program does not need to be changed, which overcomes the shortcomings of the traditional model such that the selected research data must be qualified typical data and have many information parameters. In order to use the original data for modeling analysis to predict the change of the later subsidence, we need the observation data recorded in the previous period to be exponential.

(3) The advantage of the Asaoka method (Shaogang method) is that it is possible to calculate the settlement value with a relatively low error by relying on a relatively small amount of settlement observation data, which can save a lot of time, and at the same time, it can also determine the time for the settlement to enter the subconsolidation stage. The biggest disadvantage of making judgments and calculations is that the estimated value of the final settlement depends too much on the division of the time interval. If the division of the time interval is not clear, it may cause the final prediction result to deviate greatly from the actual value.

(4) The artificial neural grid method can regard the traditional independent variables and dependent variables as input and output and use nonlinear mapping to replace the traditional complex functional relationship, which can deal with nonlinear problems well, and have good data simulation combined ability. The artificial neural network method has a very strong adaptability and can adjust the learning ability with the change of the external environment. On the other hand, the neural network has a relatively strong fault tolerance ability, the prediction and recognition speed is relatively fast, and there is no need to consider characteristic factors in the prediction process complex relationship with the target to be predicted. However, in the actual prediction process, the number of samples is determined based on experience because the neural network method does not have an effective criterion.

(5) The traditional method of predicting foundation settlement has more or less its own shortcomings and deficiencies: the preparatory work in the early stage is very heavy, not only need to deal with a large amount of information, but also a lot of repetitive work to make the work. The efficiency is relatively low, especially when encountering a lot of data and information; it becomes very difficult to process, and some data cannot be processed at all. In order to avoid these shortcomings, it is necessary to scientifically manage the settlement of soft soil foundations. A large amount of monitoring data information and reasonable selection and establishment of prediction models can improve work efficiency so as to better serve engineering construction.

3. Predictive Models and Theory

3.1. Support Vector Machines. Support vector machines (SVM) is a supervised learning model that analyzes data between classification and regression analysis. Its basic idea is to define a linear classifier with the largest margin in the function space. SVM classifiers also include kernel techniques that allow nonlinear classification. The learning strategy of the SVM classifier is the optimal classification hyperplane, in which this hyperplane must meet the classification requirements and maximize the blank space on both sides of the hyperplane while ensuring the classification accuracy. The main idea of SVM is as follows: given a set of data sets $T = \{(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)\}$, where $x_i \in R^n$, $y_i \in \{-1, +1\}$, $i = 1, 2, \ldots, N$, satisfying

$$y_i(w \cdot x_i + b) \geq 1, \tag{2}$$

make

$$\min_{w,b} \frac{w^2}{2}. \tag{3}$$

According to Lagrangian duality, the optimal solution can be obtained by solving the dual problem of the original problem, which is transformed into

$$\begin{cases} \max\limits_{\alpha}\left(\dfrac{1}{2}\sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N}\alpha_i\alpha_j y_i y_j\left(x_i \cdot x_j\right) + \sum\limits_{j=1}^{N}\alpha_i\right), \\ s.t. \quad \sum\limits_{j=1}^{N}\alpha_i y_i = 0, \\ \alpha_i \geq 0,\ i = 1, 2, \ldots, N. \end{cases} \tag{4}$$

After adding a negative sign to the target formula, the problem of solving the maximum value is converted into the problem of the minimum value. After conversion, it is

$$\begin{cases} \min\limits_{\alpha}\left(\dfrac{1}{2}\sum\limits_{i=1}^{N}\sum\limits_{j=1}^{N}\alpha_i\alpha_j y_i y_j\left(x_i\cdot x_j\right)-\sum\limits_{j=1}^{N}\alpha_i\right), \\ s.t. \quad \sum\limits_{j=1}^{N}\alpha_i y_i = 0, \\ \alpha_i \geq 0,\ i = 1, 2, \ldots, N. \end{cases} \tag{5}$$

After calculating the solution α, we further solve w and b according to α and obtain the maximum separation hyperplane and classification decision function.

3.2. Improved Artificial Bee Colony Algorithm. Aiming at the problem that the Artificial Bee Colony algorithm (ABC) algorithm has low search efficiency and is prone to generate local optimal solutions, this paper proposes an improved ABC algorithm based on two-dimensional unified population initialization and Euclidean distance update of food sources, thereby improving the search rate and efficiency of the ABC algorithm. Convergence: the specific steps are as follows.

Step 1: Initialize the population. According to the results of many experiments, the value of the kernel parameter γ is [0, 0.01], and the range of the penalty factor C is [1, 100]. Using the two-dimensional unified method, the values of γ and C were evenly divided into 25 squares, that is, 25 initial food sources, and each square represented the range of initial food sources. The schematic diagram of the initial food source range is shown in Figure 1. When the picker bee leaves the local optimal solution, it finds the square without optimal solution in all squares, randomly generates the optimal solution in the remaining squares, and uses the scout bee to search.

Step 2: Update the food source. First, optimize the penalty factor C and the kernel function parameter γ, and then express the Euclidean distance between the food source (C_1, γ_1) and the food source (C_2, γ_2), as shown in

$$d = \sqrt{\left(C_1 - C_2\right)^2 + \left(\gamma_1 - \gamma_2\right)^2}. \tag{6}$$

The traditional ABC algorithm generates new food sources as shown in

$$v_{ij} = x_{ij} + \varphi_{ij}\left(x_{ij} - x_{kj}\right). \tag{7}$$

The scout bee selects the food source as shown in

$$\mathrm{P}_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n}. \tag{8}$$

$$fit_i = \begin{cases} \dfrac{1}{1 + fit_i},\ fit_i \geq 0, \\ 1 + abs\left(fit_i\right),\ fit_i < 0. \end{cases} \tag{9}$$

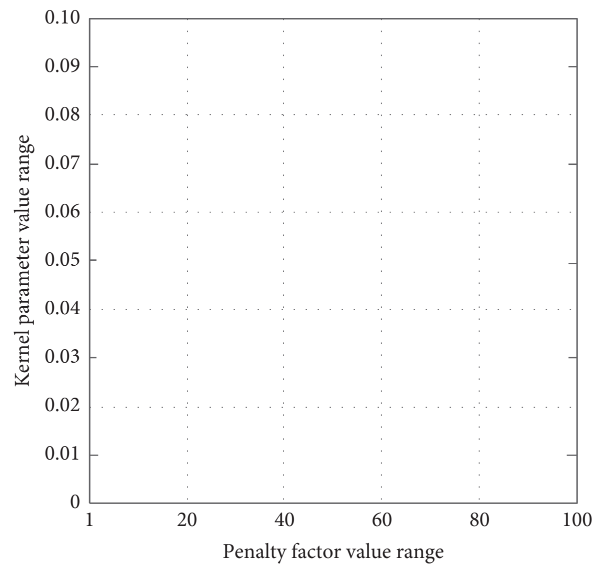

Figure 1: Schematic diagram of the range of initial food sources.

In the formula: $j \in [1,2,\ldots,D]$, $k \in [1,2,\ldots,\mathrm{SN}]$, $\varphi\_ij \in [-1,1]$, these parameters are randomly selected; fit_i is the fitness value. If the value of φ_{ij} is small, it means that the search range of bees is small, and the algorithm does not converge or leads to early convergence; otherwise, it is easy to ignore the optimal solution, which affects the convergence on this basis, so it is improved.

Step 3: Define $\Delta_i = d_i/d_{\max}$ and take the value [0, 1], where d_i represents the distance between the current solution and the optimal solution. We substitute vertex (1, 0) and vertex (100, 0.1) into formula (5) to obtain $d_{\max}$. The updated solution of the food source is automatically adjusted by the value of Δ_{i}. If the value of Δ_{i} is small, it means that the range of finding solutions is also small; otherwise, the range is large. By using this method, the number of updates is effectively reduced. By substituting the Δ_{i} value, the updated food source is shown in

$$v_{ij} = x_{ij} + \Delta_{\mathrm{i}} \cdot \varphi_{ij}\left(x_{ij} - x_{kj}\right). \tag{10}$$

3.3. Improved ABC Algorithm to Optimize SVM. The value range of the kernel parameter γ is defined as [0, 0.01], and the penalty factor C is [1, 100]. Therefore, the improved algorithm flow is shown in Figure 2, and the steps are as follows:

Step 1: Initialize the parameters of the ABC algorithm. The parameters are as follows: food source, control parameter limit, the number of bee colonies, and the maximum number of updates.

Step 2: Initialize the parameters (C, γ) in the SVM model.

Step 3: Initialize the food sources in the search range of (C, γ) using a two-dimensional uniform pair, the obtained solution is used as the input of the SVM model, and the output is the algorithm fitness.

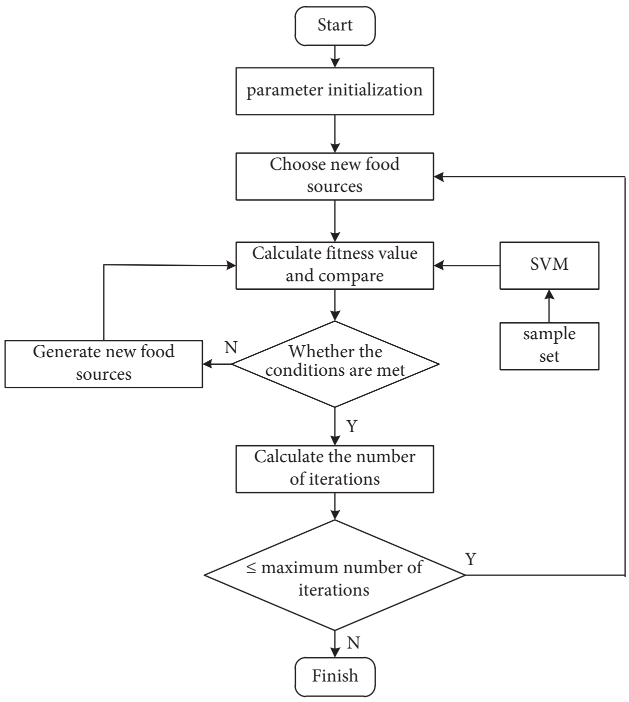

Figure 2: Optimization flow chart.

Step 4: According to formula (10), select the nearest food source to collect honey to obtain the fitness value and then compare with the previous value to retain the high fitness value.

Step 5: According to formula (8), the scout bee selects the food source. If the food source at this position has been selected by other bees, the scout bee continues to search for the food source, obtains the fitness value, and then compares it with the previous value.

3.4. Autoregressive Model. Autoregressive model (AR) models are also known as time series models. For a stable, normal, zero-mean time series $x(k)$, the autoregressive model is

$$x(k) = \sum_{i=1}^{n} a_i x(k-i) + v(k), \tag{11}$$

where $v(k)$ is a white noise sequence with zero mean.

The AR autoregressive model needs to determine the end n of the model and the parameter sequence $\{a_i\}$. The parameter series is generally estimated by the small square method. In formula (11), let $k = n + 1$, $n + 2$,...,N, and we can get formula

$$\begin{cases} x(n+1) = a_1 x(n) + a_2 x(n-1) + .. + v(n+1) \\ x(n+2) = a_1 x(n+1) + a_2 x(n) + .. + v(n+2) \\ \ldots \\ x(N) = a_1 x(N-1) + a_2 x(N-1) + .. + v(N). \end{cases} \tag{12}$$

Then use the least squares method to get

$$A_N = \left(B_N^T B_N\right)^{-1} \cdot B_N^T \cdot C_N, \tag{13}$$

where

$$\begin{aligned} A_N &= [a_1, a_2, \ldots, a_n]^T, \\ B_N &= \begin{bmatrix} x(n) & x(n-1) & \ldots & x(1) \\ x(n+1) & x(n) & \ldots & x(2) \\ \ldots & \ldots & \ldots & \ldots \\ x(N-1) & x(N-2) & \ldots & x(N-n) \end{bmatrix}, \\ C_N &= [x(n+1), x(n+2), \ldots, x(N)]^T. \end{aligned} \tag{14}$$

The parameter estimates are obtained to obtain the AR autoregressive model.

$$x(k) = \sum_{i=1}^{n} a_i x(k-i). \tag{15}$$

Use the above function to make predictions on the sequence. For the determination of the model end n, the minimum information criterion (AIC) is used, that is,

$$AIC(n) = p \ln \sigma^2 + 2n. \tag{16}$$

In the formula, p is the total number of sequence data; σ^2 is the residual equation of order. Let the minimum value of (16) corresponding to n be the optimal order.

3.5. ABC-SVM Combined with AR Model. From the perspective of subsidence analysis, the observed data can be divided into trend and random quantities, and the characteristics of a large number of surface subsidence monitoring data show that the subsidence is composed of two parts: the trend quantity and the random quantity of subsidence, that is,

$$s_i = a_i + b_i. \tag{17}$$

In the formula, s_i is the amount of settlement; a_i is the trend of settlement; b_i is the random amount of settlement. However, the core idea of the SVM model is to transform the input into a high-dimensional space through nonlinear transformation and obtain a unique optimal solution, so that the trend term can be accurately determined. The AR model is more suitable for analyzing stationary random quantities. Therefore, the combination of SVM and the respective characteristics of AR establish the SVM-AR model.

$$S_i = A_i + B_i. \tag{18}$$

In the formula, S_i is the sedimentation amount; A_i is the SVM predicted trend amount; B_i is the AR model predicted random amount.

The prediction steps of the SVM-AR model are as follows.

(1) Using n observations of sedimentation, an SVM model is established, the predicted trend value A is obtained, and the residual value x_i is calculated.

(2) Using the residual value x, find the minimum value of the minimum information criterion AIC, determine the optimal order n of the AR model, and use

Table 1: Measured value of typical subgrade section settlement.

Time (d)	Measured value (mm)	Time (d)	Measured value (mm)
215	74.9	221	134.2
232	86.3	253	145.2
271	96.2	294	148.3
302	104.8	314	154.7
321	108.1	336	159.9
359	118.6	375	167.8

Table 2: SVM model prediction results.

Time (d)	Measured value (mm)	SVM predictive value (mm)	Relative error (%)
253	145.2	141.8	2.31
294	148.3	145.2	1.67
314	154.7	150.7	2.08
336	159.9	156.1	2.31
375	167.8	163.9	2.27

the least squares method to obtain the model AR, thereby obtaining the settlement random item B_i.

(3) Using formula (18), the sedimentation amount is obtained.

4. Case Application Analysis

This paper is based on the Wujiang section of the Sujiahang Expressway. The length of the highway is 50KM. There are a lot of waters in this range, the altitude is low, and the terrain is flat. As much as 92% of the total length of the roadbed is soft soil foundation, the soft soil buried depth is generally more than 20 m, even up to 33 m, mostly silt or silt soil, with high compressibility and low strength. In this paper, a typical section is taken as an example of the average settlement of the top surface of K86 + 520. The observed data are shown in Table 1.

In this paper, the SVM model is used for conventional prediction first, and then the improved ABC algorithm is used to optimize the SVM model prediction for comparison. First, the first seven subsidence data were used as training samples to construct the model structure, and the last five subsidence data were used as test samples for the predicted value of the model. The SVM model was used to predict the data, and cross-validation was used to select the optimal parameters.

The prediction results of the SVM model are shown in Table 2.

$A_i = (80.15, 85.56, 92.14, 100.57, 104.78, 114.25, 123.41, 128.91)$ from the above SVM model. The corresponding residuals $x_i = (-4.34, 0.26, 1.57, 3.71, 2.08, 3.59, 3.98, 4.51)$. Using MATLAB programming to get the minimum $AIC = 36.7$, AR order $n = 2$, that is, the model AR (2), so as to get the prediction random item $B_i = (3.09, 3.41, 3.45, 3.45)$, the SVM-AR prediction result can be obtained; see Table 3.

In order to facilitate comprehensive analysis, the prediction results of the above example SVM and SVM-AR models are plotted, and the results are shown in Figure 3.

Table 3: SVM-AR model prediction results.

Time (d)	Measured value (mm)	SVM-AR predictive value (mm)	Relative error (%)
253	145.2	145.8	0.41
294	148.3	148.2	0.12
314	154.7	154.6	0.08
336	159.9	159.7	0.21
375	167.8	167.9	0.09

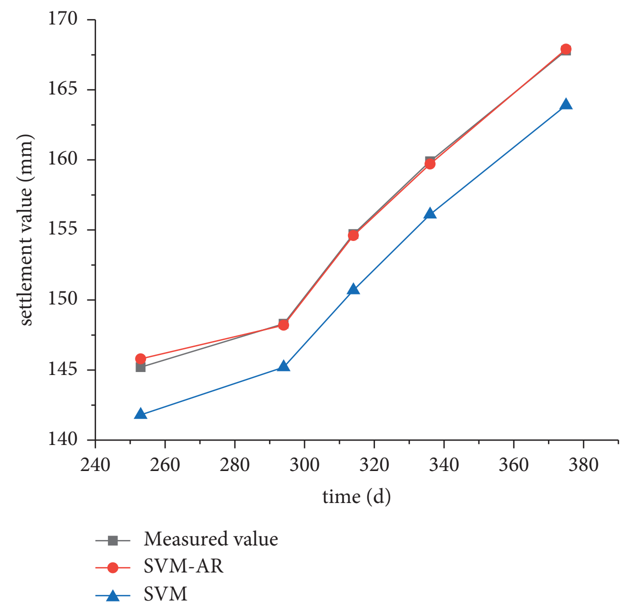

Figure 3: Comparison of predicted values between SVM-AR and SVM.

From the above calculation results, it can be seen that the SVM-AR model extracts the trend term of the subgrade settlement and conducts time series analysis on the residual, so the fitting results not only contain the trend of settlement development but also the randomness of the settlement process. It can be seen that SVM-AR (the model prediction accuracy) is better than the SVM model.

5. Conclusion

In this paper, the SVM-AR model is proposed by analyzing the characteristics of settlement data, which introduces a new viewpoint and method for predicting the settlement of highway soft soil foundation; the SVM and AR model based on ABC optimization are used to predict the foundation settlement, and the optimized SVM model extracts the trend item and the AR model extracts the random item; the foundation settlement can be accurately predicted with less parameters and a simple model form, and the prediction accuracy of the optimized SVM-AR model is significantly improved than that of the single model SVM model, so the optimized SVM-AR can better reflect the settlement process of highway soft soil foundation. The example verification shows that SVM-AR is more accurate than the SVM model prediction results and better reflects the settlement process of highway soft soil foundation. Soft soil foundations widely exist in the engineering field. SVM-AR can accurately predict the settlement process of highway soft soil foundations. However, further research is needed on the accuracy of soft soil foundation settlement prediction in other projects.

Data Availability

The data set can be accessed upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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