Prediction of Long-Term Seawall Settlement Based on Least Squares Support Vector Machine

Guo-chang GE\textsuperscript{1}\textsuperscript{*} and Fang-yi JIN\textsuperscript{2}

\textsuperscript{1}Zhejiang Institute of Hydraulics & Estuary, Hangzhou 310020, China
\textsuperscript{2}Wenzhou Oufei Economic Development Investment Co. Ltd., Wenzhou 325025, China
\textsuperscript{*}zjggc2007@163.com

Abstract. In this study, the basic principle of the least squares support vector machine (LS-SVM) method was introduced systematically. The method was applied in a seawall engineering project to establish a prediction model of long-term seawall settlement based on the LS-SVM method, and the model parameters were optimized based on the genetic algorithm. Based on the monitoring data of seawall settlement during the construction of a soft foundation seawall project in Wenzhou, China, a sample was selected to train the model, and the predicted value of long-term settlement calculated by the model was compared with the measured sample value. The results show that, with highly accurate and reliable prediction results, the prediction model of long-term seawall settlement based on the LS-SVM method possesses great application value.

1. Introduction
Nonlinear methods like the Asaoka method\textsuperscript{[1]}, the grey system theory\textsuperscript{[2]}, and the artificial neural network method\textsuperscript{[3]} are currently the main approaches to predict seawall settlement based on real-time monitoring data gained at the project site. These methods consider the actual conditions of the seawall project and are therefore widely applied in the prediction and design of seawall settlement, yet they also have some shortcomings. For example, the Asaoka method can only predict the final settlement under a specific level of load and cannot make full use of the monitoring data of seawall settlement under multiple levels of load. The grey system theory requires the original data to satisfy the smooth discrete function, which is inconsistent with the complicated construction process of a seawall project. The artificial neural network method usually takes a long time to train the samples, and it is susceptible to local extremums. In addition, as it is based on the principle of empirical risk minimization, over-fitting is likely to happen when the dimension of the sample is too high.

The support vector machine (SVM)\textsuperscript{[4]} is a machine learning method established by Vapnic in 1995 based on the statistical learning theory. The SVM method is not suitable for large samples because its computational complexity will increase as the sample size increases. Suykens et al. proposed the LS-SVM method\textsuperscript{[5]} to significantly reduce the computation time for large samples. This method has been applied in other engineering fields and achieved good predictive effects\textsuperscript{[6-8]}.

In recent years—with great attention from the Chinese government to prediction of settlement of seawall, and much progress made in the monitoring technology—systematic and advanced settlement monitoring equipment has been used for the construction of most seawall projects. Nevertheless, though accurate on-site settlement data can be monitored, there lacks an effective monitoring analysis
method, which makes the monitoring system and information unable to perform their functions. Therefore, in this study, the LS-SVM method was introduced in the prediction and analysis of the long-term settlement of seawall to fully consider the non-linearity of the settlement of the foundation soil, identify the historical pattern of the seawall’s settling volume monitored in real time, and accurately predict and judge the long-term settlement of seawall. The prediction model was evaluated based on its performance in practical application to seawall construction.

2. LS-SVM-based Settlement Prediction Model

2.1. Least Squares Support Vector Machine

For the LS-SVM, it is assumed that the initial n-dimensional settlement sample vector\((x_1,y_1),\ldots,(x_i,y_i)\in \mathbb{R}^n\) is obtained by actual measurement, where \(x_i\) is the factor influencing the settlement and \(y_i\) is the settling amount. After the sample training, a non-linear mapping function \(\psi(\cdot)\) was selected to map the sample vectors into the feature space \(\psi(x_i) = (\psi(x_1),\ldots,\psi(x_n))\), and the optimal decision function was constructed in this high-dimensional space.

\[
f(x) = w^T \psi(x) + b
\]

where \(w\) refers to the weight of variables, \(b\) denotes the bias factor, and \(\psi(x)\) stands for the mapping function.

Based on the principle of structural risk minimization, the function optimization problem of SVM\(^9\) is Formula (2):

\[
\begin{align*}
\min J(w,\xi) &= \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{l} \xi_i \\
\text{s.t. } &\gamma_i \geq w^T \psi(x_i) + b + \xi_i, \quad i = 1, 2, \ldots, l
\end{align*}
\]

where \(\gamma\) stands for the penalty factor and \(\xi_i\) denotes the slack variable.

The LS-SVM method proposed by Suykens et al. improved the function optimization method by replacing inequality constraints with equality constraints.

\[
\begin{align*}
\min J(w,\xi) &= \frac{1}{2} w^T w + \frac{1}{2} \gamma \sum_{i=1}^{l} \xi_i^2 \\
\text{s.t. } &\gamma = w^T \psi(x_i) + b + \xi_i, \quad i = 1, 2, \ldots, l
\end{align*}
\]

The Lagrange method was used to solve this problem. LS-SVM simplifies the quadratic regression of the standard SVM into a problem of solving a system of linear equations:

\[
\begin{bmatrix}
0 & 1 & \cdots & 1 \\
1 & K(x_1) + 1/\gamma & \cdots & K(x_1)
\vdots & \vdots & \ddots & \vdots \\
1 & K(x_i) & \cdots & K(x_i) + 1/\gamma
\end{bmatrix}
\begin{bmatrix}
\alpha_1 \\
\vdots \\
\alpha_i \\
\vdots \\
\vdots
\begin{bmatrix}
b \\
y_1 \\
\vdots \\
y_i \\
\vdots
\end{bmatrix}
\end{bmatrix}
\]

where \(\alpha = [\alpha_1, \alpha_2, \ldots, \alpha_n]\) is the Lagrange multiplier and \(K(x_i)\) is the symmetric kernel function satisfying the Mercer condition. Solving the above equation yields the LS-SVM prediction model.

\[
f(x) = \sum_{i=1}^{N} \alpha_i K(x_i) + b
\]

The above principle shows that the kernel function \(K(x_i)\) has the most direct impact on the performance of LS-SVM. In this study, the radial basis function (RBF)\(^{10}\) was selected because of the strong non-linear mapping ability.

\[
K(x_i) = \exp((-x_i)^2 / -2\sigma^2)
\]
where $\sigma$ is the width of the RBF.

2.2. Parameter Optimization of the Prediction Model

Once the kernel function of LS-SVM was determined, the selection of two key parameters of the model, $\gamma$ and $\sigma$, would determine the accuracy and computational complexity of the whole prediction model. Therefore, the genetic algorithm was used in this study to conduct an optimizing search of parameters for the LS-SVM model. In the process of searching, the root mean square error (RMSE)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y}_i)^2}$$

of samples was used as the fitness value of the function. Fig.1 shows the calculation steps to optimize parameters of the prediction model.

![Figure 1. Flowchart of parameter optimization of LS-SVM Model](image)

3. Engineering Application

3.1. Overview

To test the effectiveness of the LS-SVM method in predicting small data, the real-time monitoring data of seawall settlement during the construction of a soft foundation seawall project in Wenzhou was taken as an example to be analyzed in this study. As revealed by drilling, the geological layer of the seawall was mainly composed of a thick muddy layer and a silty clay layer. With high water content and low permeability, it was a typical soft foundation seawall project.

In order to monitor the deformation and stability of the seawall embankment during the construction in real time and ensure the construction safety, 10 sections of the seawall were selected for in situ observation. The 1+350 section was the master control section for ground surface settlement observation, and the filling of this section started in June 2011. To ensure the average daily settlement rate of the foundation was lower than the controlled amount, the construction of seawall was completed by stratified multi-stage filling. For instance, a total of 10 loadings were carried out at the seawall axis, and the number of multi-stage loadings generally decreased from the embankment axis towards the enclosure area and the outer sea. The construction of this section was completed in May 2014.

3.2. Data Collection
During the seawall construction, the compression and deformation of the foundation soil were observed through the settlement plate at the ground surface. Figure 2 shows how the settlement plate (ET1-ET6) was laid out in the 1+350 section. A 100 cm × 100 cm × 1 cm steel plate was used as the settlement plate and was buried before the seawall was riprapped. Exposed above ground about 1.2 m, the measuring rod was covered by a protective tube. Before loading at each stage, the area around the protective tube was filled to above the expected thickness of filling and conspicuously marked to prevent man-made damage. Set in a stable area, the base point for observing ground surface settlement was protected by reliable devices and regularly calibrated.

![Figure 2. Settlement plates in the 1+350 section Xiaomendao Reclamation Project of Wenzhou](image)

ET4 was the embankment axis measuring point of the 1+350 section and had the most complicated loading method. A total of 224 sets of settlement monitoring data during a total of 2,232 days from the date when the construction started to the completion of construction and to July 2017 were selected as the analysis object. The optimal interval time to monitor the settlement was determined to be 10d. To make it convenient to calculate, the data points were numbered per the monitoring time, \( n = 1, 2, \ldots, 224 \), and the cumulative settlement time series at the seawall measuring point was obtained (Figure 3).

![Figure 3. Cumulative settlement time series in the 1+350 section](image)

3.3. Prediction

Taking the above monitoring data as the training sample, the genetic algorithm was applied to conduct a training to optimize \( \sigma \) and \( \gamma \), the two key parameters of the LS-SVM model. First, an initial population containing the two parameters was randomly generated in MATLAB with \( M = 50 \). The training sample was input into the model, and the LS-SVM algorithm was used to calculate the fitness value of each individual in the population. The individual with the highest fitness value was selected to determine whether it met the requirements. If not, an interlace operation of the population would be carried out with the probability \( P_c \) being 0.8 and the mutation probability \( P_M \) in the process was set to 0.02. Interlace operation and mutation operation iterations were conducted in this way to obtain
better, new generations of parameters until their fitness values met the requirements. After 100 iterative computations were carried out on the parameter population in MATLAB, the genetic optimization curve of the RMPE of fitness curve of each generation of parameter population was obtained as shown in Figure 4. It can be seen that the calculation converged after 57 iterations, and the optimal parameters of the model were $\gamma = 394.017$ and $\sigma = 0.467$.

After the optimization of the parameters of the prediction model, the computation of the prediction model was simplified, and its accuracy was greatly improved as well. At this point, the first 156 sets of settlement data measured at the embankment axis measuring point of the $1+350$ section were selected and input into the optimized LS-SVM prediction model for training. Sixty-eight measured data points obtained after the loading of the seawall monitoring point was completed were selected to test the accuracy of the LS-SVM prediction model. Figure 5 shows the comparison of the overall time series of the prediction results obtained by the prediction model and the measured settlement values. The relative errors between the prediction values and the actual values are shown in Table 1.

As shown in Figure 5 and Table 1, the predicted curve fit well with the actual settlement curve, the minimum relative error between the predicted settlement in the last 680 days obtained by the LS-SVM prediction model and the actual settlement was $0.014\%$, and the maximum was only $2.454\%$. In general, the seawall settlement prediction model based on the LS-SVM method learned the historical characteristics and patterns of seawall settlement well and gave a reliable prediction of the future settlement of the seawall. However, with the passage of time, the prediction error will become larger and larger. Therefore, if the LS-SVM model is to be used for more accurate long-term prediction of seawall settlement, it is necessary to monitor the settlement of seawall accordingly and continuously update the input training samples to achieve long-term prediction.
Table1. Error of the predicted result of LS-VSM Predictive model

| Sample sequence | Relative error /% | Sample sequence | Relative error /% | Sample sequence | Relative error /% |
|-----------------|-------------------|-----------------|-------------------|-----------------|-------------------|
| 156             | 0.250             | 179             | 0.250             | 202             | 1.222             |
| 157             | 0.253             | 180             | 0.269             | 203             | 1.304             |
| 158             | 0.236             | 181             | 0.290             | 204             | 1.371             |
| 159             | 0.208             | 182             | 0.310             | 205             | 1.426             |
| 160             | 0.175             | 183             | 0.330             | 206             | 1.471             |
| 161             | 0.142             | 184             | 0.348             | 207             | 1.510             |
| 162             | 0.114             | 185             | 0.364             | 208             | 1.548             |
| 163             | 0.096             | 186             | 0.378             | 209             | 1.587             |
| 164             | 0.085             | 187             | 0.392             | 210             | 1.633             |
| 165             | 0.075             | 188             | 0.410             | 211             | 1.688             |
| 166             | 0.059             | 189             | 0.432             | 212             | 1.747             |
| 167             | 0.040             | 190             | 0.461             | 213             | 1.807             |
| 168             | 0.014             | 191             | 0.496             | 214             | 1.867             |
| 169             | 0.022             | 192             | 0.536             | 215             | 1.929             |
| 170             | 0.066             | 193             | 0.580             | 216             | 1.991             |
| 171             | 0.110             | 194             | 0.622             | 217             | 2.053             |
| 172             | 0.149             | 195             | 0.665             | 218             | 2.117             |
| 173             | 0.177             | 196             | 0.715             | 219             | 2.182             |
| 174             | 0.195             | 197             | 0.780             | 220             | 2.248             |
| 175             | 0.205             | 198             | 0.861             | 221             | 2.316             |
| 176             | 0.213             | 199             | 0.949             | 222             | 2.384             |
| 177             | 0.221             | 200             | 1.041             | 223             | 2.454             |
| 178             | 0.233             | 201             | 1.133             |                 |                   |

4. Summary
In this study, the LS-SVM algorithm was applied to the prediction of seawall settlement. The excellent non-linear generalization ability of the LS-SVM method optimized by the genetic algorithm was used to analyze the monitoring data of seawall settlement during the construction of a soft foundation seawall project in Wenzhou, and predict the future settlement. Through comparison with the actual monitoring samples, it was found that the seawall settlement prediction model based on the LS-SVM method is accurate, and the prediction results are stable and reliable. Therefore, this method is an effective and accurate method to carry out prediction of long-term seawall settlement. Due to its great application potential in the construction of seawall projects, the proposed method should be further researched.

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