Research Article

Shield Tunneling Parameter Matching Model and UI Interface

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Received 29 October 2019; Revised 21 January 2020; Accepted 28 January 2020; Published 18 February 2020

Academic Editor: Castorina S. Vieira

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In order to improve the accuracy of shield tunneling parameter matching under the limited data, the matching model based on support vector machine (SVM) and exponential adjustment inertia weight immune particle swarm optimization (EAIW-IPSO) is proposed. The nonlinear relationship model between the tunneling parameters and the ground settlement is constructed by SVM and trained with the actual engineering sample data. Based on the trained model, EAIW-IPSO is used to optimize the tunneling parameters. At the same time, UI interface was developed based on the tunneling parameter matching model. The matching model based on BP neural network and PSO algorithm is compared in simulation experiments and engineering case. It is verified that the matching model based on SVM and EAIW-IPSO still maintains great accuracy and stability as the number of samples continues to decrease. The paper provides a better solution for the matching of tunneling parameters in actual engineering.

1. Introduction

The shield construction technology is widely used in tunnel construction in China due to its low construction cost, wide application range, and low disturbance to the surrounding environment [1–3]. Since the whole construction process is located in the underground space, the safety is very important. In addition, with the improvement of construction quality requirements, more and more factors need to be considered [4]. As for shield tunnel construction, the ground settlement control is the key among all the influencing factors. If the ground settlement is too large during the construction process, the soil will collapse and cause a safety accident, affecting the construction period [5]. Many factors affect ground subsidence [6], such as the tunnel shape and diameter, the engineering geological conditions at the location, the hydrological conditions, the level of construction technology, and the level of construction management. Some of these influencing factors are uncontrollable. Some influencing factors have little impact on the construction phase once the plan is determined. Among the controllable factors, tunneling parameters have the greatest impact on ground settlement during construction [7]. Therefore, how to effectively control the ground settlement by selecting shield tunneling parameters needs to be further studied.

In practical engineering, it is difficult to establish mathematical expressions for the nonlinear relationship between tunneling parameters and ground settlement accurately. Therefore, shield tunneling parameter matching belongs to a class of nonlinear single-objective optimization problems that are difficult to establish objective functions accurately. At present, many scholars combined machine learning and intelligence optimization algorithms to solve such problems. In order to control the earth pressure balance of the shield enclosure in real time, Liu et al. [8] established a relationship model about the process parameters, rolling power, and austenite grain diameter by the neural network. Based on the trained model, the ideal point method was applied to convert it into a single-objective optimization problem. And then genetic algorithm performs parameter optimization. Aiming to match the optimal construction parameters of super-large diameter earth pressure balance shield, Qiang [9] established the relationship model between the construction parameters and the ground settlement above the tunnel axis based on BP neural network. And then shield tunneling parameters are optimized by genetic algorithm. Based on the neural network and PSO algorithm, Yan et al. [10] improved the accuracy in measuring the elastic constant of carbon/carbon composite materials successfully. Xu and Li [11] sought to find the optimal

production tank voltage and corresponding production conditions with the aim of reducing the production cost of electrolytic aluminum. The neural network was used to establish a prediction model for the relationship between the voltage and the influencing factors of the electrolytic aluminum tank. Based on the prediction model, Cell voltage optimization was performed using genetic algorithm.

The abovementioned solutions are adopted to deal with the nonlinear single-objective programming problems which are difficult to establish the objective function accurately. It is known that the performance of the nonlinear relationship prediction model and the optimization algorithm will affect the final results. The training of the nonlinear relationship prediction model is based on actual sample data. Because the economics of obtaining samples needs to be considered in engineering, the number of the obtained samples is also limited. Therefore, it is critical to obtain a better training model under the limited sample data.

To solve the shield tunneling parameter matching with the limited sample data, this paper proposes a model based on SVM and EAIW-IPSO. The SVM is used to construct the nonlinear relationship model between the tunneling parameters and the ground settlement. EAIW-IPSO is adopted to optimize the tunneling parameters. The paper studies the performance of the model when the number of training samples is decreasing. Meanwhile, the corresponding UI interface is developed. The study not only provides a better solution for shield tunneling parameter matching under the limited sample data in actual engineering but also realizes the interface operation to achieve the tunneling parameter matching conveniently.

2. Basic Theory

2.1. Analysis of SVM and Its Parameter Selection. In the 1990s, Professor Vapnik first proposed the SVM algorithm, which is based on the development of statistical learning theory. Both SVM and neural networks are machine learning algorithms [12, 13]. Compared to the neural network, SVM has better improvements in local minimum values, network structure, convergence speed, and training sample size requirements [14].

The parameters involved in the SVM mainly include loss function parameters ϵ , penalty factor C , and parameters in the kernel function [15].

- (1) The loss function parameter ϵ affects the number of vectors and the generalization ability of the training, usually ranging from 0.001 to 0.1.
- (2) The penalty factor C is the tolerance to the error. The bigger the value of C , the higher the accuracy of the training model. The smaller the value of C , the stronger the generalization ability.
- (3) This study adopted the radial basis kernel function that has a parameter σ . The value of the parameter σ is generally in the range of 0.1 to 3.8.

In this study, genetic algorithms are used to select these parameter values in the SVM.

2.2. EAIW-IPSO Algorithm. The PSO algorithm proposed by Eberhart and Kennedy in 1995 is one of the computational intelligent optimization algorithms [16]. In PSO algorithm, particle velocity and position are continuously adjusted according to the optimal particle in the search space [17]. The adjustment for particle velocity and position is mainly achieved by two extreme values [18]. One is the best solution that the particle itself obtained during the adjustment process, namely, the individual extremum. The other is the optimal solution that the entire particle population finds in all previous iterations, namely, the global extremum [19]. The adjustment equation for particle velocity and position is [20]

$$v_{is} = \omega v_{is} + c_1 r_1 (p_{is} - x_{is}) + c_2 r_2 (p_{gs} - x_{is}), \quad (1)$$

$$x_{is} = x_{is} + v_{is}, \quad (2)$$

where v_{is} is the velocity of the i th particle in the s th direction ($i = 1, 2, \dots, M$) ($s = 1, 2, \dots, N$); ω is inertia weight; c_1 and c_2 are acceleration factors; r_1 and r_2 are random values at $(0, 1)$; p_{is} is the individual extremum; and p_{gs} is the group extremum.

In PSO algorithm, the particle lacks mechanism of variation and only relies on the interaction between particles. In the iterative process, it is easy to fall into local extremum. The trajectory of the whole iterative process is sinusoidal wave swing [21]. The early iteration speed is faster, the later speed is slowed down, and even the stagnation phenomenon occurs, which makes the algorithm have “premature” phenomenon. Thus, the overall search ability is weak.

In order to improve the performance of the PSO algorithm, Hou et al. [22] improved the inertia weight adjustment equation and the population variation mechanism, proposing the EAIW-IPSO algorithm. EAIW-IPSO algorithm has higher accuracy in both single-peak and multi-peak problems and has great stability. The new population variation mechanism in EAIW-IPSO algorithm reduces the possibility of the algorithm falling into local extremes. In addition, EAIW-IPSO algorithm can quickly converge near the optimal value in the early stage of iteration and perform the optimal value search in late period, which shows that EAIW-IPSO has better iterative characteristics. Therefore, this paper applies EAIW-IPSO algorithm to optimize the shield tunneling parameters. The inertia weight adjustment equation in the EAIW-IPSO algorithm is

$$\omega = \omega_{\min} \left(\frac{\omega_{\max}}{\omega_{\min}} \right)^{(1-(t/T)^2)}, \quad (3)$$

where $\omega_{\min}$ is minimum inertia weight; $\omega_{\max}$ is maximum inertia weight; t is the current number of iterations; and T is maximum number of iterations.

The population variation strategy in the EAIW-IPSO algorithm is before the next iteration and another particle population with size of M is regenerated. Among the original and new populations, M particles with larger fitness values are selected from the $2M$ particles as the group of the next iteration. The others are eliminated.

EAIW-IPSO algorithm specific process:

Step 1: set the value of all parameters, including M , T , c_1 , c_2 , $\omega_{\min}$, and $\omega_{\max}$.

Step 2: initialize the position and velocity values and calculate the fitness value of each particle.

Step 3: adjust the position and velocity values based on equations (1)–(3) and set the personal and global best position.

Step 4: initialize another particle group with size of M . M particles with larger fitness values are selected from the $2M$ particles as the group of the next iteration, updating the global best position.

Step 5: the next iteration is entered. If the termination condition is satisfied, the iterations stop.

3. Shield Tunneling Parameter Matching Model and Its Performance Verification

3.1. Matching Model Based on SVM and EAIW-IPSO. In order to better predict the nonlinear relationship between the tunneling parameters and ground settlement in actual engineering, formation and geometric condition parameters are considered in the study. Set the number including tunneling parameters, formation, and geometric condition parameters to m $\{x_1, x_2, \dots, x_m\}$. The objective function value is the ground settlement value D . n groups of training samples $(X(j), d(j))$ ($j = 1, 2, \dots, n$) are obtained through the tunneling test section. Map the above sets of training samples to a high-dimensional (l -dimensional) feature space and use the following function for linear regression [15]:

$$D(\mathbf{X}) = \mathbf{u}^T \boldsymbol{\varphi}(\mathbf{X}) + b, \quad (4)$$

where u is an l -dimensional weight vector, $\mathbf{X}$ is a set with m parameter variables, $\boldsymbol{\varphi}(\mathbf{X})$ is a mapping function, and b is an offset term.

The abovementioned regression problem is transformed into the optimal value by using the ε insensitive loss function. The converted optimal value problem is as follows:

$$\min F(u, b, \xi, \xi^*) = \left\{ \frac{1}{2} \|\mathbf{u}\|^2 + C \sum_{j=1}^n (\xi_j^* + \xi_j) \right\}, \quad (5)$$

subject to

$$\begin{aligned} d^{(j)} - \mathbf{u}^T \boldsymbol{\varphi}(\mathbf{X}^{(j)}) - b &\leq \varepsilon + \xi_j^*, \quad j \in [1, n], \\ \mathbf{u}^T \boldsymbol{\varphi}(\mathbf{X}^{(j)}) + b - d^{(j)} &\leq \varepsilon + \xi_j, \quad j \in [1, n], \\ \xi_j, \xi_j^* &\geq 0, \quad j \in [1, n], \end{aligned} \quad (6)$$

where ξ_j and ξ_j^* are relaxation factors, C is a penalty factor, and ε is a loss function parameter.

Introducing the nonnegative Lagrangian multipliers α_j , α_j^* , η_j , and η_j^* to transform equation (5) into the following form:

$$\begin{aligned} R(\mathbf{u}, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*) &= \frac{1}{2} \|\mathbf{u}\|^2 + C \sum_{j=1}^n (\xi_j^* + \xi_j) \\ &\quad - \sum_{j=1}^n \alpha_j [\varepsilon + \xi_j + d^{(j)} - \mathbf{u}^T \boldsymbol{\varphi}(\mathbf{X}^{(j)}) - b] \\ &\quad - \sum_{j=1}^n \alpha_j^* [\varepsilon + \xi_j^* - d^{(j)} + \mathbf{u}^T \boldsymbol{\varphi}(\mathbf{X}^{(j)}) + b] \\ &\quad - \sum_{j=1}^n (\eta_j^* \xi_j^* + \eta_j \xi_j). \end{aligned} \quad (7)$$

Equation (7) derivation of ω , b , ξ_j , and ξ_j^* :

$$\frac{\partial R(\mathbf{u}, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*)}{\partial \mathbf{u}} = \mathbf{u} - \sum_{j=1}^n (\alpha_j^* - \alpha_j) \boldsymbol{\varphi}(\mathbf{X}^{(j)}) = 0, \quad (8)$$

$$\frac{\partial R(u, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*)}{\partial b} = \sum_{j=1}^n (\alpha_j^* - \alpha_j) = 0, \quad (9)$$

$$\frac{\partial R(u, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*)}{\partial \xi_j} = C - \alpha_j - \eta_j = 0, \quad j \in [1, n], \quad (10)$$

$$\frac{\partial R(u, b, \xi, \xi^*, \alpha, \alpha^*, \eta, \eta^*)}{\partial \xi_j^*} = C - \alpha_j^* - \eta_j^* = 0, \quad j \in [1, n]. \quad (11)$$

Replace the corresponding variables in equation (7) with equations (8)–(11) and get the dual problem as follows:

$$\begin{aligned} \min Q(\alpha, \alpha^*) &= \frac{1}{2} \sum_{i,j=1}^n (\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) K(\mathbf{X}^{(i)}, \mathbf{X}^{(j)}) \\ &\quad + \varepsilon \sum_{i=1}^n (\alpha_i^* + \alpha_i) - \sum_{i=1}^n d^{(i)} (\alpha_i^* - \alpha_i), \end{aligned} \quad (12)$$

subject to

$$\begin{aligned} \sum_{j=1}^n (\alpha_j^* - \alpha_j) &= 0, \\ 0 \leq \alpha_j^* &\leq C, \quad j \in [1, n], \\ 0 \leq \alpha_j &\leq C, \quad j \in [1, n]. \end{aligned} \quad (13)$$

The appropriate kernel function is selected. In addition, the genetic algorithm is used to select the values including ε , C , and kernel function parameters. The optimal solution is obtained:

$$\alpha = (\alpha_1, \alpha_1^*, \dots, \alpha_n, \alpha_n^*)^T. \quad (14)$$

Using the Karush–Kuhn–Tucker conditions (KKT) condition to get value of b , and the result is

$$b = d^{(j)} - \sum_{i=1}^n (\alpha_i^* - \alpha_i) K(\mathbf{X}^{(i)}, \mathbf{X}^{(j)}) \pm \varepsilon. \quad (15)$$

The value of b is averaged, and the SVM model, that is, ultimately applied to predict the nonlinear relationship between selected parameters (tunneling parameters, formation, and geometric condition parameters) and ground settlement is

$$D(\mathbf{X}) = \sum_{j=1}^n (\alpha_j^* - \alpha_j) K(\mathbf{X}^{(j)}, \mathbf{X}) + \bar{b}. \quad (16)$$

The EAIW-IPSO algorithm is used to optimize the tunneling parameters. Since the number of the selected parameter variables is m , each particle spatial position consists of these m parameter variables and the particle space dimension is m . The formation and geometric condition parameter values are artificially unadjustable. Thus, the maximum and minimum parameter values are set equal to each other. The particle population size is set to G . Initialize the parameter variable values for each group. $\mathbf{X}^{(s)} = (x_1^{(s)}, x_2^{(s)}, \dots, x_m^{(s)})$ ($s \in \{1, 2, \dots, G\}$). In addition, each particle speed needs to initialize. $\mathbf{V}^{(s)} = (v_1^{(s)}, v_2^{(s)}, \dots, v_m^{(s)})$ ($s \in \{1, 2, \dots, G\}$).

Using the SVM model obtained from training to calculate the ground settlement value corresponding to each parameter variable set $d(\mathbf{X}^{(s)})$ ($s \in \{1, 2, \dots, G\}$), the reciprocal of the settlement value is taken as the fitness value of the parameter variable set:

$$d(\mathbf{X}^{(s)}) = \sum_{j=1}^n (\alpha_j^* - \alpha_j) K(\mathbf{X}^{(j)}, \mathbf{X}^{(s)}) + \bar{b}, \quad (17)$$

$$\text{fitness}(s) = \frac{1}{d(\mathbf{X}^{(s)})}.$$

subject to

$$\begin{aligned} 0 &\leq c_1(\mathbf{X}) \leq 92, \\ 90 &\leq c_2(\mathbf{X}) \leq 110, \\ 20 &\leq c_3(\mathbf{X}) \leq 25, \\ c_1(\mathbf{X}) &= 85.334407 + 0.005686x_2x_5 + 0.00026x_1x_4 - 0.002205x_3x_5, \\ c_2(\mathbf{X}) &= 80.51249 + 0.007132x_2x_5 + 0.002996x_1x_2 + 0.002181x_3^2, \\ c_3(\mathbf{X}) &= 9.300961 + 0.004703x_3x_5 + 0.001255x_1x_3 + 0.001909x_3x_4, \\ x_1 &\in [78, 102], x_2 \in [33, 45], x_3 \in [27, 45], x_4 \in [27, 45], x_5 \in [27, 45]. \end{aligned} \quad (19)$$

200 variable value sets and corresponding objective function values are obtained according to the objective function and constraints. In the experiment, 5 variable value sets are reduced at a time until the set number is reduced to half of the original number. The training sample sets with different numbers can be obtained and applied to test the performance of the matching model based on SVM and EAIW-IPSO. Through simulation experiments, the total error of the prediction system (MSE) and the relative error of

Take each parameter variable set as the individual extremum of the corresponding particle $\mathbf{P}^{(s)} = (p_1^{(s)}, p_2^{(s)}, \dots, p_m^{(s)}) = (x_1^{(s)}, x_2^{(s)}, \dots, x_m^{(s)})$ ($s \in \{1, 2, \dots, G\}$). The parameter variable set with the biggest fitness value is used as the group extremum $\mathbf{P}^{(g)} = (p_1^{(g)}, p_2^{(g)}, \dots, p_m^{(g)}) = (x_1^{(g)}, x_2^{(g)}, \dots, x_m^{(g)})$.

Update $v_i^{(s)}$ and $x_i^{(s)}$ ($s \in \{1, 2, \dots, G\}$, $i \in \{1, 2, \dots, m\}$) according to equations (1)–(3). After the update, each parameter variable value needs to be checked within the value range. If it is out of range, it is reinitialized. The fitness value corresponding to the updated parameter variable set is calculated. The individual and group extreme values are updated.

Then, other G parameter variable sets are generated, calculating the corresponding fitness values and setting individual extreme values. G parameter variable sets with higher fitness values are selected and used as the particle population of the next iteration. Update individual and group extremum and loop iterative process until the number of iterations ends.

3.2. Model Performance Verification. Two examples were selected to study the performance of the model based on SVM and EAIW-IPSO. In the experiment, the performance of the model was observed by continuously reducing the number of training samples. At the same time, the results were compared with model based on BP and PSO.

Case 1.

$$\min f(\mathbf{X}) = 5.3578547x_3^2 + 37.293239x_1 - 40792.141, \quad (18)$$

the objective function value are obtained and shown in Table 1.

The above mentioned data is plotted in Figures 1(a) and 1(b). From Figure 1(a), the values of MSE based on SVM are all lower than 0.01. The values of MSE based on BP neural network are all above 0.04. Therefore, when the sample size is gradually reduced from 200 to 100, the prediction model based on SVM still keeps high accuracy. In addition, according to variation of curves from SVM

TABLE 1: Experimental results of the two models for the first case.

Number of samples	SVM and EAIW-IPSO		BP and PSO	
	MSE	Relative error	MSE	Relative error
200	0.0024	0.0043	0.0475	0.0191
195	0.0025	0.0043	0.0461	0.0141
190	0.0026	0.0043	0.0526	0.0266
185	0.0027	0.0044	0.0968	0.0362
180	0.0027	0.0043	0.0459	0.0086
175	0.003	0.0047	0.0757	0.0376
170	0.0031	0.0045	0.0847	0.0238
165	0.0034	0.0047	0.0648	0.0392
160	0.0036	0.0051	0.0718	0.0263
155	0.0036	0.0049	0.0434	0.0274
150	0.0039	0.0050	0.0821	0.0106
145	0.0041	0.0052	0.0652	0.0097
140	0.0041	0.0050	0.0826	0.0305
135	0.0042	0.0047	0.0571	0.0137
130	0.0042	0.0045	0.0704	0.0220
125	0.0044	0.0049	0.049	0.0059
120	0.0045	0.0040	0.0715	0.0232
115	0.0045	0.0040	0.0464	0.0199
110	0.0049	0.0039	0.0442	0.0168
105	0.0051	0.0043	0.0897	0.0222
100	0.0057	0.0070	0.0698	0.0143

(a)

(b)

FIGURE 1: Experimental results for the first case under different sample sizes: (a) the sample size and MSE; (b) the sample size and the corresponding relative error of the optimal objective function value.

and BP, it can be found that the curve based on SVM is significantly smaller as the number of samples continues to decrease, which shows that the SVM has better stability in the case of relatively small sample size. Thus, the prediction model based on SVM has better comprehensive performance.

According to Figure 1(b), the relative error curve of the optimized objective function value based on SVM and EAIW-IPSO algorithm has small fluctuations of about 0.005.

The relative error curve based on BP and PSO algorithm are over the curve based on SVM and EAIW-IPSO algorithm. The maximum relative error based on BP and PSO algorithm is close to 0.04. Therefore, the accuracy of the matching model based on SVM and EAIW-IPSO algorithm is better. In addition, it can be seen from the curve fluctuation that the curve variation based on SVM and EAIW-IPSO algorithm is significantly smaller. These results show that the model based on SVM and EAIW-IPSO algorithm still maintains

high accuracy and stability when the number of training sample is small.

Case 2.

$$\min f(\mathbf{X}) = \frac{1}{2}x_1^2 + x_2^2 - x_1x_2 - 2x_1 - 6x_2, \quad (20)$$

subject to

$$\begin{aligned} x_1 + x_2 &\leq 2, \\ x_1 - 2x_2 &\geq -2, \\ 2x_1 + x_2 &\leq 3, \\ x_1 &\geq 0, \\ x_2 &\geq 0. \end{aligned} \quad (21)$$

100 variable value sets and corresponding objective function values are obtained according to the objective function and constraints. The number of variable values is reduced by 5 at a time until the number of variable value sets is reduced to half of the original number. 11 sets with different number of training samples can be obtained. The results are shown in Table 2.

The abovementioned data is plotted in Figures 2(a) and 2(b). It is known that the values of MSE based on SVM are always lower than that based on BP neural network in Figure 2(a). Meanwhile, the maximum value of MSE based on BP is close to 0.08. The values of MSE based on SVM are all lower than 0.01. The difference between the maximum and minimum values of the MSE is 0.0006 based on SVM. Another is 0.051 based on BP neural network. These data also show that the SVM has better accuracy and stability in the case of relatively small sample size.

In Figure 2(b), it shows that the variation of curve based on SVM and EAIW-IPSO algorithm is significantly smaller than that based on BP and PSO algorithm. In addition, the curve of the former is below the curve of the latter. These results also verify the performance of the model based on SVM and EAIW-IPSO.

Therefore, the results from these two experiments all show that the matching model based on SVM and EAIW-IPSO not only has high accuracy but also has better stability. This model can solve the parameter matching in the case of relatively small sample size.

3.3. UI Interface of Shield Tunneling Parameter Matching Module. Based on the proposed shield parameter matching model, the UI interface of the tunneling parameter matching module was developed. The development language is C# and the development environment is Visual Studio 2012. The window UI interface is designed by Windows Forms technology. The UI interface of the module is mainly composed of four tabPage pages, and the corresponding functions are reading and processing of training sample data, training of the SVM predictive model, testing of the SVM predictive model, and optimization of tunneling parameters.

Reading and processing of the training sample: the training sample data including the selected parameters and the surface settlement values in the .txt file are read by the data stream. Meanwhile, the data are normalized and displayed on the interface for the personnel to view. It should be noted that the data needs to be arranged in a certain format.

Training of the SVM prediction model: based on the genetic algorithm and support vector machine theory knowledge, the button from the UI interface is used to select the corresponding training parameters, train the model, and analyze the results. The genetic algorithm iterative process and the fit to the training sample are displayed by the chart control.

Test of the SVM prediction model: the test sample is read through the data stream and displayed in the interface. The ground settlement values corresponding to the selected parameter in the test sample is calculated based on the prediction model and compared with the actual ground settlement values. Therefore, the model generalization ability can be analyzed.

Optimization of tunneling parameters: based on the trained prediction model, the proposed EAIW-IPSO algorithm theory knowledge is used to optimize the shield tunneling parameters. Each variable range is added through the ListBox control in the interface. The optimization result is displayed in the TextBox, and the optimization process is displayed through the chart control.

4. Case Study

The shield section of Shenwan Metro Line 2 between the Shenwan town to Wuyi Square is selected. The data in this section is used to test the model performance in practical application and feasibility of the UI interface. Therefore, based on the data obtained in the literature [23], 34 groups of samples in which the maximum settlement values are all less than 10 mm were randomly acquired. The selected parameter sample values are shown in Table 3. The first 30 groups were applied to train the model and the last 4 groups were used as test samples.

The selected geometric condition parameters is the ratio of buried depth H and diameter excavation D . Formation condition parameters are groundwater level, cohesion, internal friction angle, earthwork heavy, and side-pressure coefficient. The tunneling parameters are synchronous grouting amount, shield thrust, cutter head torque, the ratio of tunneling speed and cutter speed R (the cutter speed is usually 1.5 rad/min), and earth pressure [24, 25].

4.1. Implementation of Tunneling Parameter Matching by UI Interface Based on SVM and EAIW-IPSO Model. In the SVM, the radial basis function is selected [26]. The loss function parameter ε , the penalty factor C , and the σ in the kernel function are optimized by genetic algorithm [27, 28]. The reading interface of the training sample is shown in Figure 3. The specific values including the iteration number, population size, crossover probability, and mutation probability in the genetic algorithm are shown in Figure 4. The SVM

TABLE 2: Experimental results of the two models for the second case.

Number of samples	SVM and IPSO		BP and PSO	
	MSE	Relative error	MSE	Relative error
100	0.0003	0.0010	0.0342	0.0095
95	0.0003	0.0008	0.0279	0.0055
90	0.0004	0.0020	0.0294	0.0037
85	0.0004	0.0016	0.0275	0.0094
80	0.0004	0.0022	0.065	0.0298
75	0.0003	0.0017	0.0637	0.0267
70	0.0004	0.0017	0.0701	0.0113
65	0.0004	0.0024	0.0363	0.0168
60	0.0005	0.0019	0.0514	0.0396
55	0.0008	0.0014	0.0785	0.0479
50	0.0009	0.0022	0.0633	0.0320

FIGURE 2: Experimental results for the second case under different sample sizes: (a) the sample size and MSE; (b) the sample size and the corresponding relative error of the optimal objective function value.

model is trained based on the training samples. The MSE is 0.0295. The fitting curves of training samples are shown in Figure 4 too. The predicted value curve and the actual value curve are basically merged. The model fits the training sample better.

The test results for the trained SVM model are as follows: the relative error values are all lower than 10% except for one group. The average value of the relative error is 5.98%. Therefore, the generalization ability of the model that is applied to build the relationship between the selected parameters and ground settlement is also better.

Based on the obtained SVM model, the tunneling parameters from the tunnel section in Table 4 are optimized. The related parameter values in EAIW-IPSO are set [29]. The optimization results are shown in Figure 5.

The obtained optimization tunneling parameter values based on SVM and EAIW-IPSO are shown in Table 5. The corresponding maximum ground settlement is 5.3 mm.

4.2. Implementation of Tunneling Parameter Matching by UI Interface Based on BP and PSO Model. The initial weight of BP neural network is selected by genetic algorithm. The number of nodes in the input layer and output layer are 11 and 1, respectively. The number of nodes in the hidden layer is finally determined to be 3 by multiple experiments. The number of iterations is 1000 [30]. Based on the training samples, the BP neural network model is trained. The MSE is 0.4652. The fitting curve based on BP neural network is shown in Figure 6. It can be seen from the figure that the predictive effect is poorly around the 5th sample point. Moreover, it is also not well between the 10th sample point and the 20th sample point. Therefore, the effect of the BP neural network is relatively poor in the case of the limited number of samples.

The generalization ability test of the BP neural network model was carried out. The maximum and average relative errors are 36.55% and 12.72%, respectively.

TABLE 3: Sample data.

Geometric factors	Formation factors				Tunneling parameters				Maximum settlement (mm)		
	Groundwater level (m)	Earthwork heavy (kN)	Cohesion (kPa)	Internal friction angle (°)	Side-pressure coefficient	Synchronous grouting amount (m³)	Shield thrust (kN)	Cutter head torque (kN·m)		Earth pressure (Bar)	R (mm)
H/D	5.13	20.01	63.12	27.16	0.34	6.2	7375	1575.56	0.95	32.96	9.34
2.65	9	20.37	62.48	24.63	0.33	6.3	8383.33	1821.61	0.95	33.49	8.12
2.7	9.58	20.62	66.3	25.21	0.33	6.2	8711.11	1663.33	1.06	36.35	7.54
2.81	13.34	19.73	53.29	22.15	0.34	6.4	8452.94	1597.41	1.14	36.21	3.67
2.9	10.72	19.27	47.33	17.22	0.4	7.4	13636.3	2851.82	1.43	35.94	5.61
3.21	2.53	19.21	44.42	17.29	0.41	6.7	11961.1	2501.89	1.39	38.23	9.26
3.21	2.78	19.81	41.09	17.62	0.41	5.6	11361.1	2320.56	1.44	40.85	6.21
4.24	19.16	20.22	72.22	23.81	0.3	11.13	10057.25	2515.18	1.16	21.53	4.23
3.93	17.51	20.92	67.04	24.66	0.3	7.47	11442.94	1649.41	1.35	27.65	3.77
4.06	17.96	20.31	71.25	25.42	0.29	7.57	9044.44	2516.67	1.28	15.46	5.42
3.93	17.74	21.04	55.52	24.95	0.3	9.87	10070.94	1741.18	1.15	27.02	3.4
3.21	10.46	19.41	46.07	20.32	0.4	7.2	13111.7	2939.41	1.3	30.08	4.25
3.81	16.78	19.37	65.47	19.42	0.3	9.1	10468.71	2602.35	1.09	31.41	5.07
3.8	17.38	21.45	58.1	22.97	0.28	7.37	8144.44	2654.44	1.09	17.8	4.44
3.62	17.2	20.88	65.95	22.45	0.29	8.13	9794.24	2301.76	1.17	36.16	4.67
3.63	17.16	21.11	66.3	23.51	0.28	9.66	8594.12	2564.71	1.11	20.67	6.02
3.59	17.5	20.44	75.26	24.59	0.3	8.37	10059.41	2161.18	1.04	32.12	3.84
3.61	17.93	20.97	72.62	22.85	0.3	7.27	9083.33	2233.33	1.22	26.85	4.28
3.52	16.35	21.2	76.54	23.95	0.3	10.43	11553.11	2740.56	1.09	31.15	4.32
3.48	16.7	20.27	64.48	23.29	0.28	9.03	10889.53	2531.76	1.12	32.86	4.44
3.53	16.91	20.9	64.38	22.51	0.3	8.97	12838.89	2511.11	1.26	23.33	6.75
3.45	17.4	21.26	64.85	24.26	0.3	8.53	9702	2222.35	1.13	33.1	9.83
3.5	16.71	20.99	64.94	22.87	0.3	9.17	10911.11	2394.44	1.06	28.33	7.76
3.42	17.1	21.32	58.19	24.54	0.3	10.1	12803.41	2675.88	1.14	29.88	8.87
3.37	16.3	21.29	65.95	24.37	0.3	8.7	11662	2707.65	1	28.24	9.54
3.43	17.89	21.11	62.66	23.42	0.3	9.03	13900	2513.89	1.09	21.33	8.54
3.4	18.3	21.31	46.11	24.34	0.3	9.7	13194.44	2491.67	1.12	24.63	7.81
2.63	5.46	19.89	63.82	24.58	0.37	6.2	7658.82	505.31	0.81	30	7.43
2.65	7.25	20.09	70.64	28.8	0.33	6	7572.22	1697.22	0.84	39.21	7.65
2.64	7.5	19.85	45.23	24.99	0.35	5.7	7370.59	1388.82	0.84	28.48	6.54
3.94	17.98	20.5	58.21	25.54	0.3	8.13	8700	2682.35	1.15	17.76	4.76
2.7	9.25	19.59	63.79	20.14	0.39	6.2	7616.67	1442.22	0.99	33.39	6.56
3.36	17.44	21.21	54.52	23.95	0.3	9.1	10211.11	2388.89	1.07	33.15	9.64
3.34	17.5	20.95	47.97	22.66	0.3	8.77	11102.82	2611.18	0.96	34.43	8.56

FIGURE 3: The reading interface of the training sample.

FIGURE 4: The interface of the SVM model training.

TABLE 4: Geometric and formation condition parameter values.

Tunnel section	H/D	Groundwater level (m)	Earthwork heavy (kN)	Cohesion (kPa)	Internal friction angle (°)	Side-pressure coefficient
DK24+222 right	1.99	8.1	19.36	47.06	15.07	0.48

FIGURE 5: The interface of the parameter optimization based on EAIW-IPSO.

TABLE 5: Optimization results based on SVM and EAIW-IPSO.

Tunneling parameter	Synchronous grouting amount (m ³)	Shield thrust (kN)	Cutter head torque (kN·m)	Earth pressure (Bar)	Driving speed (mm/min)
Optimization values	5.11	9108.37	1020.37	1.02	30.33

FIGURE 6: The interface of the BP model training.

FIGURE 7: The interface of the parameter optimization based on PSO.

TABLE 6: Optimization results based on BP and PSO.

Tunneling parameter	Synchronous grouting amount (m^3)	Shield thrust (kN)	Cutter head torque ($\text{kN}\cdot\text{m}$)	Earth pressure (Bar)	Driving speed (mm/min)
Optimization values	9.85	9748.23	1148.23	1.99	30.45

Based on the BP neural network model, the tunneling parameters of the section in Table 4 are also optimized. The optimization results are shown in Figure 7 and Table 6.

4.3. Comparative Analysis for Two Models

4.3.1. Fitting of Training Samples. It can be seen from Figures 4 and 6, the SVM model has better fitting effect in the case of relatively small sample size. The predicted value curve and the actual value curve can be basically merged. But the BP neural network model has poor fitting effect in some of the sample points, and the overall predicted effect is not well. In addition, the MSE based on SVM is smaller than that based on BP neural network.

4.3.2. Model Generalization Performance. The model prediction accuracy provides an important basis for subsequent parameter optimization. Therefore, it is very important to improve the generalization ability of the model. The maximum predicted relative error based on SVM for the test

sample is 13.87%, and the average relative prediction error is 5.98%. While the maximum predicted relative error based on the BP neural network is 36.55% and the average value is 12.72%. It can be seen that the generalization ability of the SVM is better than that of the BP neural network when the number of training samples is limited.

4.3.3. Optimization Results. The optimal target value based on SVM and EAIW-IPSO model is 5.3 mm, and the optimal target value based on BP neural network and PSO model is 6.52 mm. The optimization results shows that the tunneling parameter values obtained by the model based on SVM and EAIW-IPSO can minimize the ground settlement value within the range of factors considered.

In actual construction, there are many factors in the construction site. It is difficult to quantify and consider all the factors at present. Therefore, the obtained tunneling parameter values need further adjustment in engineering application. The performance requirements for the matching model are relatively high. Thus, the proposed model based

on SVM and EAIW-IPSO provides a more effective way for the selection of actual tunneling parameters, avoids the blindness of the selection, and provides a more reliable guarantee for the control of ground subsidence risk.

5. Conclusions

- (1) In order to improve the reliability and accuracy for the tunneling parameter selection under the limited data, the model based on SVM and EAIW-IPSO algorithm is proposed and constructed.
- (2) In the simulation examples, it is verified that the parameter matching model based on SVM and EAIW-IPSO can maintain high accuracy and stability as the number of samples continues to decrease. Meanwhile, based on the parameter matching model of SVM and EAIW-IPSO, the corresponding tunneling parameter matching UI interface was developed to realize the interface operation.
- (3) The application in actual engineering case also verified that the model based on SVM and EAIW-IPSO is superior in sample fitting, model generalization ability, and optimization result. Therefore, the proposed model provides a more effective solution for tunneling parameter matching in actual shield construction.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This study was partially supported by the co-funding of National Natural Science Foundation of China and Shenhua Group Corporation Ltd. (Grant no. U1261212) and Program of Major Achievements Transformation and Industrialization of Beijing Education Commission (Grant no. ZDZH20141141301). The authors would like to express their heartfelt gratitude to all the members who helped and cooperated with them.

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