Research Article

Shield Tunneling Parameters Matching Based on Support Vector Machine and Improved Particle Swarm Optimization

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Of late, emerging algorithms such as machine learning have been increasingly used in shield tunneling construction management and control. This research article proposes a shield tunneling parameter matching model based on a support vector machine (SVM) and an improved particle swarm algorithm (PSO) to enhance the accuracy and reliability of shield tunneling parameter selection. First, the optimization performance of the algorithm is augmented by adjusting particle diversity. Simulation-based experiments are conducted to test the performance of the improved algorithm. The experimental results indicate that the improved algorithm has better accuracy. Meanwhile, the particle diversity adjustment strategy is given. Then, the SVM model to express the relationship between shield tunneling parameters and ground settlement is established and trained. Based on the obtained SVM model, the improved PSO is used to optimize the tunneling parameters. The results show that the shield tunneling parameter matching model based on SVM and improved PSO can obtain more accurate shield tunneling parameters and provides a more precise reference for selecting shield tunneling parameters.

1. Introduction

With the advancement of civil construction technology, large-scale projects such as tunnels have an increasing impact on the development of the large, medium, and small cities and have made extraordinary contributions to urban economic development. However, soil loss at the tunnel entrance, soil instability at the driving face, and subsidence of the shield are common problems in shield tunneling construction. Therefore, the selection of reasonable shield tunneling parameters plays a decisive role in the smooth progress of the project. The numerous factors involved in the shield tunneling process introduce many inconveniences to selecting shield tunneling parameters. Subsequently, the shield tunneling parameters are needed to optimize the system.

Recently, machine learning algorithms are adopted in several fields such as healthcare, business, agriculture, and social media [1–4]. In the Industry 4.0 era, the digital world has a huge amount of data such as cyber security data, mobile data, business data, healthcare data, and social media data. The knowledge of artificial intelligence (AI) and machine learning (ML) plays a key role to analyze these data for the design and development of smart and automated applications. Recently, several machine learning algorithms are widely used in the field of civil engineering [5–14]. These approaches yield several prospects for the optimization of shield tunneling parameters. In addition, the works which are related to settlement prediction [15–17] using machine learning algorithms are proposed. Existing machine learning-based approaches for the optimization of shield tunneling parameters face several challenges.

The existing machine learning approaches which are based on shield tunneling parameter matching use neural networks [18], K-means [19], correlation-based algorithms [20], and Bayesian networks [21]. These algorithms are failed to improve the accuracy and choose the optimal shield tunneling parameters. To obtain shield tunneling parameters more quickly and accurately, the paper enhances the PSO algorithm optimization performance by improving the particle diversity. A specific strategy is proposed based on the simulation results of six classical functions. Combining
60 monitoring data points from Shanghai tunnel engineering, SVM is adopted to establish the relationship model between the surface subsidence and shield tunneling parameters. Then, based on the obtained SVM model, the improved PSO is applied to optimize the tunneling parameters.

The remaining section of the paper is structured as follows: Section 2 discusses about the state-of-the-art works related to shield tunneling parameter matching. The proposed works such as SVM-based shield tunneling parameter matching and PSO-based algorithm to enhance the accuracy and reliability of shield tunneling parameter selection are presented in Section 3. The performance verification of the PSO-based approach is briefed in Section 4. Section 5 details about shield tunneling parameter matching model based on SVM and improved PSO. An extensive case study which is pertaining to the shield tunneling parameter matching approach is elaborated in Section 6. Section 7 explained about discussion and conclusion which is associated with this research work.

2. Literature Review

Within the context of the rapid development of information technology, researchers have improved machine learning algorithms to varying degrees and gradually applied them in several fields [1–4]. Of late, intelligent algorithms are gradually being widely used in the field of civil engineering [5–8], providing an opportunity for the optimization of shield tunneling parameters. As one of the main tunnel construction methods [9–12], the shield method is a complex mechanical process of undisturbed soil damage and reshaping. Since the excavated soil is subjected to shear and extrusion of the cutter head and grouting pressure of shield tail soil, different degrees of settlement and deformation are inevitably caused. At the same time, Shanghai, Hangzhou, Wenzhou, and other coastal cities in China are primarily in soft soil areas with poor antideformation ability. The settlement has a significant impact on tunnel construction to varying degrees, causing heavy economic losses and threatening human life safety [13, 14]. Therefore, the shield construction settlement has become the main problem endangering the health of subway and highway tunnels.

In recent years, the major geotechnical problem caused by shield construction has attracted the attention of many researchers. Chen et al. [15] combined actual engineering data to build a model. Comparing six machine learning algorithms with traditional multiple linear regression methods, this article discussed the potential and advantages of machine learning algorithms in settlement prediction. Scott et al. [16] optimized and enhanced the soil compressibility prediction model through the SVM algorithm. This work effectively tested the correlation performance between the compressibility index and the soil index characteristics in the settlement calculation.

Hu et al. [17] proposed an extended machine learning framework based on actual data to prove that the PSO-SVR method has the highest accuracy among the three proposed prediction algorithms. To significantly reduce the surface subsidence, the researcher has studied the shield tunneling parameters related to the surface subsidence to improve the tunnel construction level and protect human life safety.

Jing and Gang [18] established a neural network model between shield tunneling parameters and ground settlement and then optimized shield tunneling parameters through a genetic algorithm. Min and Jie [19] proposed the shield tunneling parameter analogy setting method (SAPAS). The combination of the K-means clustering algorithm and the empirical formula setting method improved the practical application effect of the empirical formula.

Tian and Ma [20] tried to use a multidimensional correlation algorithm to optimize the shield tunneling technology and established a parameter correlation model through the Apriori algorithm. Zeng et al. [21] proposed a parameter optimization method based on DBN and applied it to the tunnel project in Wuhan, China. In addition, Bo et al. [22] obtained the best tunneling parameters by utilizing onsite monitoring. These studies, however, have limitations in adjusting the neural network grid weight coefficient, which causes the model to fall into the local optimal. K-means clustering algorithm can only get the local optimal in the iteration, and Apriori algorithm I/O load is large, which will produce too many candidate-project sets and other problems.

3. Methodology

3.1. Particle Swarm Algorithm (PSO). PSO is a stochastic optimization algorithm proposed by Kennedy and Eberhart [23] to simulate biological activities in nature. As a branch of evolutionary computing, PSO has been applied to solve various engineering optimization problems. PSO is different from the genetic algorithm (GA) since GA uses bio-evolution mechanisms such as crossover and mutation operations. But PSO has no such operations. They follow the optimal particle to replace, and the PSO has fewer parameters and is easier to implement.

PSO algorithm mainly relies on two extreme values to update the speed and position. One is the overall optimal solution of all particles, called the global optimal solution $P_g = \{g_1, g_2, \ldots, g_n\}$. The other is the optimal solution of the particle itself in the entire iterative history, called the individual optimal solution $p_i = \{p_{i1}, p_{i2}, \ldots, p_{in}\}$ where $i = 1, 2, \ldots, M$. The ith particle is denoted by $x_i = [x_{i1}, x_{i2}, \ldots, x_{in}]$. The velocity of the ith particle is $v_i = [v_{i1}, v_{i2}, \ldots, v_{in}]$.

The iterative formulas are mentioned as follows: the ith particle is expressed as

$$v_{i,d} = \omega \times v_{i,d} + c_1 \gamma_1 \left(p_{i,d} - x_{i,d}\right) + c_2 \gamma_2 \left(P_g,d - x_{i,d}\right), \quad (1)$$

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

where $p_{i,d}$ is the individual optimal solution, $P_g,d$ is the global optimal solution, $\omega$ is the inertia weight, $c_1$, $c_2$ are learning factors, and $\gamma_1$, $\gamma_2$ are random numbers in the range [0, 1].

To improve the performance of PSO, the inertia weight is adjusted according to the following formula [24]:
\[
\alpha_i = (\omega_{\text{max}} - \omega_{\text{min}} - d_1)e^{t_1/\max}, \quad (3)
\]

where \(d_1\) and \(d_2\) are control factors, the purpose is to control \(\omega\) between \(\omega_{\text{max}}\) and \(\omega_{\text{min}}\). \(d_1 = 0.2, d_2 = 0.7, \omega_{\text{max}} - \omega_{\text{min}}\) takes 0.5, and \(t_{\max}\) is the maximum number of iterations.

This article further mediates the diversity of particles in PSO to improve the performance of PSO. In each iteration, particles are eliminated according to the proportion of 1/2, 1/3, 1/4, 1/5, and 1/6 to analyze the performance changes of particles, and specific improvement strategies are proposed based on the analysis results.

3.2. Support Vector Machine (SVM). SVM is a supervised machine learning method that can be used for classification and regression problems [25]. The optimal decision function is constructed by mapping input variables to a high-dimensional space based on the principle of structural risk minimization. The appropriate kernel function is helpful to reduce the increase of computational complexity caused by the mapping from low-dimensional space to high-dimensional space. The optimal solution is obtained by sample training. The regression function for SVM is as follows:

\[
f(x) = u \times \varphi(x) + b,
\]

where \(u\) is the weight vector, \(\varphi(x)\) is the mapping function, and \(b\) is the bias term.

The goal of optimization is

\[
\min_{w,b} \frac{1}{2}w^2,
\]

where points located within the boundary should satisfy \(|y_i - (\omega x_i + b)| \leq \varepsilon\).

The introduction of nonnegative Lagrange multipliers \(\alpha_i, \alpha_i^*, \eta_j, \eta_j^*\) further transforms the problem into the following equation:

\[
\mathcal{L}(w, b, \xi, \alpha, \alpha^*, \mu, \mu^*) = \frac{1}{2}w^2 + C \sum_{i=1}^{N}(\xi_i + \xi_i^*) - \sum_{i=1}^{N} \mu_i \xi_i - \sum_{i=1}^{N} \mu_i^* \xi_i^*
\]

\[
+ \sum_{i=1}^{N} \alpha_i[f(x_i) - y_i - \varepsilon - \xi_i] + \sum_{i=1}^{N} \alpha_i^*[f(x_i) - y_i - \varepsilon - \xi_i^*],
\]

where \(C\) is the penalty factor and \(\xi_i, \xi_i^*\) are relaxation factors.

The equivalent duality problem is obtained as follows:

\[
\max_{\alpha, \alpha^*} \sum_{i=1}^{N} y_i (\alpha_i^* - \alpha_i) - \sum_{i=1}^{N} x_i^T (\alpha_i^* + \alpha_i) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} [(\alpha_i^* - \alpha_i)(x_i^T x_j)(\alpha_j^* - \alpha_j)],
\]

s.t. \(\sum_{i=1}^{N} (\alpha_i^* - \alpha_i) = 0, \quad 0 \leq \alpha_i, \alpha_i^* \leq C.

Restrictions are as follows:

\[
\begin{align*}
\alpha_i \alpha_i^* &= 0, \quad \xi_i \xi_i^* = 0, \\
(C - \alpha_i) \xi_i^* &= 0, \quad (C - \alpha_i^*) \xi_i = 0, \\
\alpha_i [f(x) - y - \xi_i] &= 0, \\
\alpha_i^* [y_i - f(x) - \xi_i^*] &= 0.
\end{align*}
\]

The bias term \(b\) is solved by the Caro required-Kuhn–Tucker condition and is presented as follows:

\[
b = y^{(i)} - \sum_{j=1}^{n-k} (\alpha_j^* - \alpha_j) K(x^{(i)}, x^{(j)}) \pm \varepsilon.
\]

The final SVM regression prediction model by using quadratic programming yields

\[
f(X) = \sum_{j=1}^{n-k} (\alpha_j^* - \alpha_j) K(x^{(i)}, x) + b,
\]

where \(K(x^{(i)}, x)\) is the kernel function of the SVM.

The kernel functions commonly used in SVM are linear kernel function, polynomial kernel function, radial basis kernel function (RBF), and sigmoid kernel function. RBF kernel function has better convergence properties and is used in significant engineering prediction algorithms. Therefore, RBF is used as the kernel function for SVM models in the paper [26].

4. Improvement and Performance

4.1. Improvement Method. In PSO, particles get different feasible solutions due to particles flying at different positions. That is, the diversity of viable solutions is called population diversity. Population diversity, also known as extensiveness and uniformity in PSO, is an important measure to evaluate the ability of PSO to search for feasible solutions. Therefore, to improve the population diversity, the paper explores the adjustment strategy of particle diversity by eliminating particles in the ratio of 1/2, 1/3, 1/4, 1/5, and 1/6 each iteration.
The specific experimental improvement strategy of this work is that the particles with smaller fitness values are eliminated in the ratio of 1/2, 1/3, 1/4, 1/5, and 1/6 according to their fitness values. Furthermore, the eliminated particles are generated by initialization. The individual optimal solutions and the global optimal solution are finally updated.

4.2. Validation of the Proposed Improved Algorithm.
Experimental simulation analysis based on six benchmark functions is carried out to determine at what ratio the optimal value can be obtained. Table 1 shows the six benchmark functions.

The particle population size is 50, and the number of iterations is 200. The algorithm runs independently 15 times under each elimination ratio. The final results are shown in Tables 2–4.

Tables 1–3 show the optimal results obtained by the PSO with different elimination ratios. The minimum and average are visualized in Figures 1 and 2.

From the curves in Figures 1 and 2, F1, F2, and F4 have higher searchability when the elimination ratio is 1/2. F3, F5, and F6 are relatively close to each other regarding their searchability at each elimination ratio. The difference between each average value of the three benchmark functions F3, F5, and F6 is tiny at each elimination ratio, indicating that the improved PSO has less influence on the stability. When the elimination ratio of F1 and F2 is 1/6, the average value is quite different from other elimination ratios. Moreover, it can be seen from the figure that there is a noticeable difference in the average value of F1 under different elimination ratios, indicating the improved PSO algorithm has a significant impact on the stability of F2. Except that the proportion is 1/6, the average value difference of F4 under each elimination proportion is slight and significantly lower than other functions. This indicates that its stability is less affected by the improved PSO algorithm, and the optimization effect of the algorithm is better than other benchmark functions. According to the above analysis, it is clear from the figure that the elimination proportion of the three indicators in different functions is different, and the elimination proportion is not fixed and stable. The optimal value of each function has its own corresponding elimination proportion.

The iterations of six classical functions are shown in Figures 3 to 8. From Figure 3, the algorithm’s corresponding elimination ratio of 1/2 is significantly more substantial than the other elimination ratios in the search for superiority before the 60th iteration. Between the 80th and 100th iterations, the searchability of each elimination ratio gradually approaches and starts to enter the local search phase. After the 160th iteration, each elimination ratio slowly converges and shows a clear distinction.

From Figure 4, the elimination ratio of 1/2 in two hundred iterations has better searchability than that under other elimination ratios. Except for the elimination ratio of 1/2, the function is not stable in the other elimination ratios before 100 iterations. After iterations, it gradually enters the local search phase. The searchability of each elimination ratio also slowly becomes an obvious distinction with a large gap, and finally, the function finds the optimal value in the case of an elimination ratio of 1/2.

From Figure 5, the iteration curve declines precipitously in the early stages and enters the local search phase more quickly. Before the 80th iteration, the function had the weakest search ability at an elimination ratio of 1/2. Since the 80th iteration, the searchability at the elimination ratio of 1/2 gradually increases and finally coincides with the iteration curve at the elimination ratio of 1/3. The elimination ratio that makes the function find the optimal value is 1/4. The function characteristics are similar to F2.

From Figure 6, the iteration curve is clearly different from the other function curves. The function iteration curve as a whole decreases in a stepwise manner. At the same time, it can also be seen that the searchability at the elimination ratio of 1/4 is inferior before 50 iterations. After 50 iterations, its searchability shows a cliff-like growth. But after increasing to a certain level, there is no significant change between 60 and 160 iterations. Although it is further enhanced after the 160th iteration, it is still weaker than other elimination ratios in the end. As the elimination ratio is 1/2 for finding the optimal value, the function’s ability to find the optimal value presents the characteristics of first being decisive, then weak, and then powerful. The algorithm gradually enters the convergence stage after 100 iterations and converges at the earliest when the elimination ratio is 1/6.

It can be seen from Figure 7 that the 1/4 elimination ratio has a significant advantage over other elimination ratios before the 70th iteration. In contrast, the functions under other elimination ratios show instability, weaker merit-seeking ability, and smaller gaps. At 80 iterations, the process gradually enters the local search phase under each elimination ratio. The iteration curve begins to converge as the searchability from different elimination ratios gradually stabilizes. The 1/4 elimination ratio that shows an absolute advantage in the first period gradually becomes inferior and finally overlaps with the 1/6 elimination ratio curve. While the 1/5 elimination ratio is inadequate in the first period, it shows a significant increase. This elimination ratio finally obtains the optimal value.

In Figure 8, the algorithm converges late, gradually converges after 120 iterations in each elimination ratio. The algorithm with an elimination ratio of 1/5 converges after 160 iterations. Before the 70th iteration, the elimination proportions did not show their respective advantages. In subsequent iterations, the searchability of the algorithm with an elimination ratio of 1/3 gradually increased and finally found the optimal value. The figure also shows that the merit-seeking ability is chronically inferior throughout the 200 iterations at a 1/4 elimination ratio.

Based on the above result analysis, through the overall analysis of the six benchmark functions and the independent study of each function, the six benchmark functions obtain the optimal solution. However, it is also found that different functions have their own most appropriate elimination ratios, so the min (1/2,1/3,1/4,1/5, and 1/6) strategy is adopted to solve realistic problems. If the same optimal value is obtained under different elimination ratios, the smaller elimination ratio is taken to improve the optimal solution’s efficiency.
Table 1: Six benchmark functions used in simulation experiments.

| Number | Benchmark function | Range of search | Dimension |
|--------|--------------------|-----------------|-----------|
| 1      | \( F_1 = \sum_{i=1}^{n} x_i^2 \) | \([-10, 10]\) | 20        |
| 2      | \( F_2 = \sum_{i=1}^{n} |x_i|^{1+1} \) | \([-10, 10]\) | 20        |
| 3      | \( F_3 = \sum_{i=1}^{n} |x_i| + \prod_{i=1}^{n} |x_i| \) | \([-10, 10]\) | 20        |
| 4      | \( F_4 = \sum_{i=1}^{n} x_i^4 + \text{Gauss}(0, 1) \) | \([-1.28, 1.28]\) | 30        |
| 5      | \( F_5 = \sum_{i=1}^{n} x_i \sin(x_i) + 0.1 x_i \) | \([-10, 10]\) | 20        |
| 6      | \( F_6 = \frac{1}{4000} \sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{n} \cos(x_i + 1(x_i/\sqrt{\bar{F}})) \) | \([-200, 200]\) | 20        |

Table 2: Comparison of the minimum values of six benchmark functions.

| Elimination ratio | \( F_1 \) | \( F_2 \) | \( F_3 \) | \( F_4 \) | \( F_5 \) | \( F_6 \) |
|-------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1/2               | 1.42E-01  | 1.16E-05  | 2.539306  | 1.45E-05  | 9.05E-01  | 0.811097  |
| 1/3               | 1.65E-01  | 7.76E-05  | 2.516099  | 0.000261  | 2.1564692 | 0.581494  |
| 1/4               | 1.80E-01  | 4.28E-05  | 2.187291  | 0.000151  | 1.5639153 | 0.69168   |
| 1/5               | 2.10E-01  | 4.44E-04  | 2.882946  | 0.000355  | 0.6863804 | 0.78372   |
| 1/6               | 0.235694  | 1.91E-03  | 3.386878  | 0.00051   | 1.5755379 | 0.811097  |

Table 3: Comparison of the average values of six benchmark functions.

| Elimination ratio | \( F_1 \) | \( F_2 \) | \( F_3 \) | \( F_4 \) | \( F_5 \) | \( F_6 \) |
|-------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1/2               | 0.802178  | 1.85E+00  | 4.79E+00  | 0.002589  | 3.6622543 | 1.051938  |
| 1/3               | 9.90E-01  | 2.24E-01  | 4.552009  | 0.003068  | 3.7624239 | 0.969001  |
| 1/4               | 6.23E-01  | 7.09E-01  | 4.647805  | 0.003354  | 4.3874189 | 0.982548  |
| 1/5               | 6.71E-01  | 2.54E-01  | 5.220595  | 0.004902  | 3.8896712 | 1.000483  |
| 1/6               | 7.60E-01  | 1.67E+00  | 5.10187   | 0.224481  | 4.0006234 | 1.018506  |

Table 4: Comparison of the RMSE values of six benchmark functions.

| Elimination ratio | \( F_1 \) | \( F_2 \) | \( F_3 \) | \( F_4 \) | \( F_5 \) | \( F_6 \) |
|-------------------|-----------|-----------|-----------|-----------|-----------|-----------|
| 1/2               | 1.2287    | 5.02E+00  | 6.14E+00  | 0.004     | 4.9809    | 1.2941    |
| 1/3               | 1.63E+00  | 8.97E-01  | 5.9538    | 0.0049    | 4.8831    | 1.2038    |
| 1/4               | 8.50E-01  | 2.68E+00  | 6.0151    | 0.0068    | 5.81      | 1.2076    |
| 1/5               | 9.27E-01  | 6.11E-01  | 6.6692    | 0.0087    | 5.2275    | 1.2366    |
| 1/6               | 1.20E+00  | 4.67E+00  | 6.3881    | 0.9618    | 5.3412    | 1.2561    |

Figure 1: Six benchmark functions minimum value trend.

Figure 2: Six benchmark functions average value trend.
Figure 3: $F_1$ function iteration trend comparison analysis chart.

Figure 4: $F_2$ function iteration trend comparison analysis chart.

Figure 5: $F_3$ function iteration trend comparison analysis chart.

Figure 6: $F_4$ function iteration trend comparison analysis chart.

Figure 7: $F_5$ function iteration trend comparison analysis chart.

Figure 8: $F_6$ function iteration trend comparison analysis chart.
5. Shield Tunneling Parameter Matching Model Based on SVM and Improved PSO

5.1. Determination of Shield Tunneling Parameters. According to scholars' studies on tunneling parameters [27–32], the following parameters are the main ones affecting shield tunneling construction.

5.1.1. Soil Lateral Pressure Coefficient. The soil lateral pressure coefficient affects the soil state. The soil lateral pressure coefficient needs to be dynamically adjusted to keep the front soil in a state of passive Earth pressure. It is influenced by the surface conditions ahead and above the excavation surface. When the surface settlement is large, the soil lateral pressure coefficient needs to be increased. However, the soil lateral pressure coefficient needs to be reduced while the surface uplift is considerable.

5.1.2. Advancing Speed. The shield advancement speed influences the soil settlement in front of the shield blade. When the propulsion speed is high, the soil in front of the cutter head is easily squeezed by the soil in the soil tank and the panel, causing the surface to bulge. However, the soil in front of the cutter head will have surface settlement due to insufficient pressure at a low propulsion speed.

5.1.3. Grouting Filling Rate. Synchronous grouting is indispensable in the tunnel construction method to fill the construction gap caused by the shield in real time. Because the slurry enters the surrounding soil, the building gap cannot be filled entirely. Whether the building gap is filled will also have a significant impact on the surface. Therefore, the grouting filling rate is closely related to the surface settlement.

5.1.4. Grouting Pressure. When the grouting pressure is too enormous, it will make the slurry flow too much into the surrounding soil, which will improve the grouting rate but not the filling rate of grouting and will have a counterproductive effect. On the contrary, when the grouting pressure is too small, it will not guarantee the slurry injection. The grouting pressure needs to meet a certain pressure to complete the construction gap generated by the shield construction. At the same time, the soil near the end of the shield is uplifted by the extrusion, leaving a certain amount for subsequent consolidation and settlement.

5.1.5. Stopping Time. The shield machine will stop tunneling due to many factors during construction. At this time, the stopping time will have an impact on the surface settlement. With the extension of stopping time, the surface settlement will increase significantly.

5.2. Model Establishment. In the shield tunneling parameter matching process, it is necessary to find a set of optimal parameters within the allowable range of parameters and, finally, achieve the minimum surface settlement. However, the relationship between each tunneling parameter is mutually constrained. Many tunneling parameters cannot be expressed in a simple functional relationship with each other. SVM has the unique advantage of reflecting the complex relationship between the parameters. Therefore, it can be used to establish the relationship model between shield tunneling parameters and surface settlement. Based on the actual engineering data samples, the SVM model is trained. And then, the shield tunneling parameters are optimized by the improved PSO. The specific steps are summarized as follows:

1. Particle parameters initialization, setting population size, iteration number, learning factor in PSO, Initializing the velocity and position of the particles (shield tunneling parameters) in the PSO, setting the dimensionality and the range of particle positions according to the requirements of different problems, and calculating the particle fitness values.

2. The particle velocity and position are updated according to equations (1) and (2), respectively. Equation (3) is used to calculate the Inertia weights. The updated particle fitness values are calculated, and the individual extremes and population extremes are updated.

3. After the update is completed, the particle population is eliminated according to 1/2, 1/3, 1/4, 1/5, and 1/6 for particles with low fitness values. The eliminated particles are generated by re-initialization, and their fitness values are calculated. Individual extremes and population extremes for new particles are updated.

4. Loop step 2, step 3 until the end of the iteration condition.

5. The reciprocal of the immense fitness value is used as the final settlement optimization value. The obtained tunneling parameter values are used as a reference for final parameter adjustment in the later stage.

6. Case Study

6.1. Project Introduction. The Earth pressure balance shield machine, with a diameter of 14.27 m, is used for the Shanghai bund tunnel project. The tunnel’s total length is 1098 m [33]. The project requires high environmental protection. There are many buildings and historical preservation buildings along the tunnel, which creates many difficulties for the construction and increases the technical difficulty. In terms of geological conditions, the location traversed by the shield machine has a sandy chalk layer and clayey chalk soil interspersed with a chalky clay layer, which is prone to collapse and sand flow during excavation. In the construction process, the minimum overburden thickness during shield advance is 8.52 m which belongs to shallow overburden shield construction. This project’s shield diameter is 14.27 m, making it more difficult to control the infiltration prevention and shield axis of the cave door.
Because a shield machine with a large diameter is used, the usual experience of small diameter shield construction will not be applicable. The setting for the shield tunneling parameters will become more complex. It is necessary to take reasonable measures to set the critical shield tunneling parameters for maintaining the surrounding environment and reducing the impact on the surrounding environment and buildings along the route.

6.2. Optimization of Shield Tunneling Parameters. Sixty sets of monitoring points for the Shanghai Bund Tunnel Project are shown in Figure 9. These data are used to train the SVM model. Collection of real-time datasets in this machine learning task is challenging. So, we have chosen suitable machine learning algorithms which work better even in a small dataset. Support vector machines work better even in small samples [34, 35]. The parameters \(c\) and \(g\) in SVM were determined to be 18.5 and 2.1, respectively. It can be seen from Figure 10 that the training sample is consistent with the training output. The total error RMSE of the fitting system is 0.0844, indicating that there is good fitting. Combined with the test sample data in Table 5, the difference between the predicted and actual values is 11.8178% below 15%, proving that the model's prediction accuracy is based on SVM for the relationship between shield tunneling parameters and surface settlement is better.

The parameter value in PSO is set: population size is 50, the maximum number of iterations is 200, and the dimension is 5. The range settings for \(x_1, x_2, x_3, x_4\), and \(x_5\), which represent the soil lateral pressure coefficient, advancing speed, grouting filling rate, No6 grouting pressure, and stopping time, are [0, 2], [0, 50], [100, 200], [0, 1], and [0, 20], respectively. Optimization was conducted several times under each elimination ratio (1/2, 1/3, 1/4, 1/5, and 1/6) to obtain the minimum settlement value and corresponding optimal parameter. The fitness values were calculated based on the trained SVM model. Combining Table 6 with Figure 11, we know that under all elimination ratios, the minimum predicted value is 0 at the elimination ratios of 1/3, 1/4, 1/5, and 1/6. Five optimal
Figure 10: Training fitting diagram.

Table 5: Training samples of construction parameters and surface settlement.

| Monitoring point | Soil lateral pressure coefficient | Advancing speed (mm/min) | Grouting filling rate (%) | No6 grouting pressure (MPa) | Stopping time (h) | Final settlement (mm) | Predicted value (mm) | MAPE (%) |
|------------------|----------------------------------|--------------------------|---------------------------|-----------------------------|------------------|-----------------------|-----------------------|----------|
| B54–E            | 0.93                             | 17.2                     | 127                       | 0.4                         | 3                | −10.3                 | −9.9699               | 11.8178 |
| C27–E            | 0.85                             | 26.2                     | 99                        | 0.4                         | 5                | 11.01                 | 12.8564               | 11.8178 |
| B24–E            | 0.82                             | 21.9                     | 126                       | 0.9                         | 2.5              | −8.63                 | −9.8693               | 11.8178 |
| B40–E            | 0.98                             | 28.8                     | 126                       | 0.4                         | 2                | −9.05                 | −10.2207              | 11.8178 |

Table 6: Prediction of settlement and optimization of parameter selection.

| Monitoring point | Soil lateral pressure coefficient | Advancing speed (mm/min) | Grouting filling rate (%) | No6 grouting pressure (MPa) | Stopping time (h) | Final settlement (mm) | Predicted value (mm) | Final settlement (mm) |
|------------------|----------------------------------|--------------------------|---------------------------|-----------------------------|------------------|-----------------------|-----------------------|-----------------------|
| 1/2              | 1.026913233                      | 33.054732                | 110.2668425               | 0.511636618                 | 12.20055         | 6.075E−13              | 0                    | 6.075E−13              |
| 1/3              | 0.853638066                      | 14.598547                | 106.9142372               | 0.639073422                 | 8.968524         | 0                     | 0                    | 0                     |
| 1/4              | 1.020860055                      | 35.226181                | 100                       | 0.514805007                 | 9.179082         | 0                     | 0                    | 0                     |
| 1/5              | 0.932789942                      | 38.325932                | 128.4975161               | 0.401850619                 | 4.791962         | 0                     | 0                    | 0                     |
| 1/6              | 0.933834737                      | 21.688509                | 120.3252482               | 1                           | 9.179082         | 0                     | 0                    | 0                     |

Figure 11: Comparative analysis of the predicted trend of subsidence under each elimination ratio.
parameters are obtained as shown in Table 6, so 1/6 is taken as the elimination ratio for model prediction. Combining Tables 6 and 7, it can be seen that the improved algorithm with “elimination” can find smaller settlement values compared with the unimproved algorithm, which shows that the improved method proposed in this paper can find better settlement values and has certain research significance.

The main parameters considered in the model are soil lateral pressure coefficient, advancing speed, grouting filling rate, No6 grouting pressure, and stopping time. By combining SVM and PSO effectively, the model can obtain optimal parameter matching and the corresponding lowest settlement value. However, because the shield tunneling construction process is highly complex and involves many factors, the tunneling parameter value used in the final project needs to be further adjusted according to the optimized tunneling parameters. Therefore, the proposed match model in the paper can provide a better method for the selection of tunneling parameters in practical engineering.

7. Discussion and Conclusion

The paper first explores the strategy of adjusting particle diversity in PSO to improve the accuracy and reliability of shield tunneling parameter selection. Based on the analysis for simulation experiments, the particle diversity adjustment strategy is to take the optimal value of different elimination ratios. When the same optimal value is obtained under different elimination ratios, the smaller elimination ratio is used to improve the accuracy and efficiency of the optimal solution.

The SVM is applied to establish the nonlinear relationship between the shield tunneling parameter and the settlement value. Based on the Shanghai Bund Tunnel Project data, the SVM model is trained and tested. The result shows that the SVM model is a good fit and accurately describes the nonlinear relationship between each shield tunneling parameter and the final settlement. Finally, the improved PSO is used to optimize tunneling parameters. The improved PSO predicts that the amount of sedimentation will be close to zero. This is an ideal value. There are many other factors in practical engineering. The tunneling parameter value used in the final actual project needs to be further adjusted according to the optimized tunneling parameters.

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.

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Table 7: Prediction of settlement and optimization of parameter selection (Unimproved algorithm).

| Monitoring point | Soil lateral pressure coefficient | Advancing speed (mm/min) | Grouting filling rate (%) | No6 grouting pressure (MPa) | Stopping time (h) | Final settlement (mm) |
|-----------------|----------------------------------|--------------------------|---------------------------|-----------------------------|------------------|-----------------------|
| None            | 0.847265255                      | 31.8067857               | 133.6892641               | 1                           | 0                | 7.10543E−15           |
|                 | 0.878315843                      | 35.13572442              | 104.2519731               | 0.732968534                 | 2.181577284      | 7.10543E−15           |
|                 | 0.826208217                      | 25.56947989              | 137.0125332               | 1                           | 7.654577596      | 2.13163E−14           |
|                 | 0.863112949                      | 26.58609905              | 127.2061708               | 0.390089676                 | 20               | 5.23194E−10           |

Figure 12: Comparative analysis of improved PSO-based algorithm and unimproved algorithm in terms of prediction of the settlement amount.
