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Feedback analysis of tunnel construction using a hybrid arithmetic based on Support Vector Machine and Particle Swarm Optimisation

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ABSTRACT

Feedback controls for tunnel construction require identifying geomechanical parameters and adjusting supporting parameters, both of which are optimisation problems. This paper presents an integrated optimisation method for the feedback control of tunnel displacement; it combines the Support Vector Machine (SVM), particle swarm optimisation (PSO) and numerical analysis methods. Initially, the nonlinear relationship between parameters and displacements is efficiently represented by SVM. Numerical analysis is then used to create training and testing samples for SVM recognition. PSO is used to search on the parameters of SVM and to obtain the geomechanical and support parameters. A case study is provided to verify the proposed methodology. This study provides an alternative means for adjusting tunnel construction schemes based on field observations and the optimisation of quantitative integration.

1. Introduction

Rock displacement around a tunnel is caused by complex interactions between the rock and the tunnel construction support system. Based on many years of experience, Rabcewicz [1] of Austria proposed the famous New Austria Tunnel Method (NATM), which definitely pointed out the importance of surrounding rock deformation on tunnel construction. In fact, observation and control of surrounding rock displacement is the primary objective of the tunnel construction process [2,3]. Tezuka and Seoka [4] systematically introduced the latest technologies for engineering underground excavations in Japan and emphasised the "redesign" concept in the excavation process. Tunnel construction is essentially a feedback control process involving two correlative stages: geomechanical parameters back analysis and supporting parameter optimisation.

Because the mechanics of tunnel excavation reflect the mechanical properties of the surrounding rock, it is efficient to select parameters based on field measurements. This method is called back analysis or parameter identification. Back analysis methods are divided into three classes: the reversed solving method, the direct method and the collection of illustrative plates method. The direct method using displacement is commonly adopted to determine geomechanical parameters in rock engineering [5–12]. Zhu and Wang [13] proposed applying back analysis to tunnel engineering with a dynamic construction theory for underground engineering. They studied the optimal construction scheme for cavern groups using dynamic programming, which improved on previous studies of construction optimisation sequences. In addition, An and Feng [14,15] combined the evolution-finite element, artificial neural network and parallel computation methods for intelligent cavern group optimisation. This method has been used to optimise the soft rock replacement scheme for an underground powerhouse hydroelectric power station in China.

Typical methods such as the Powell method, Gauss Newton method, Bayesian method, and Genetic Algorithm have been proposed for obtaining optimal parameters from displacement measurements [16–18]. However, two problems with the tunnel optimisation method remain completely unresolved. First, because calculations are done in a large space and are highly multi-modal, they cannot be solved by some calculus-based and enumerative techniques. In addition, the highly non-linear and complex relationship between the INPUT and OUTPUT of tunnel construction complicates and slows numerical simulations. Therefore, a powerful model with a faster simulation time is needed to study this non-linear relation.

Particle Swarm Optimisation (PSO) and Support Vector Machine (SVM), the latest computational intelligence algorithms, have been increasingly focused based on their performance [19–26]. Begambre and Laier [20] used PSO to study structural damage identification; Pereza and Behdinan [21] detailed a PSO algorithm that is suitable for optimising structural constraints; Lute et al. [24] used SVM to predict the flutter derivatives for any bridge deck size based on wind tunnel experimental data; M.Y. Cheng [25] proposed an Evolutionary SVM combining genetic algorithms and SVM to create an Evolutionary SVM

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Inference System (ESIS); and Samui [26] used SVM to study the settlement of shallow foundations on cohesionless soils.

In the present study, the tunnel construction process is regarded as a self-adaptation control process [16]. Orthogonal design and numerical simulation were used to develop a new intelligent displacement optimisation control method, which incorporates a support vector machine and particle swarm optimisation. As a case study, the proposed method was applied to the optimisation of shotcrete parameters for a typical tunnel.

2. Particle Swarm Optimisation and Support Vector Machine

2.1. Particle Swarm Optimisation

PSO is a global optimisation method proposed by Kennedy and Eberhart [19] to solve nonlinear global optimisation objectives. It is based on the swarm behaviour of birds or fishes around food. The term "particle" is used here to refer to the individual candidate in the PSO solution process. Fundamentally, it is assumed that each actor will benefit from the experiences of both itself and the group. As an iterative optimisation tool, PSO is similar to Genetic Algorithm methods in that the system is initialised as a group of stochastic solutions and the optimised solution is found by iteration. However, the particles do not have the crossover and mutation operations; they move following the optimal particles. Each solution of the optimisation problem is considered a particle, which is like a bird. In addition, each particle has a fitness value determined by the optimisation function in PSO and a direction and distance determined by its velocity. The two extreme values are tracked by the particles in each iteration. The first point is the optimal solution out of all of the particles throughout the searching history: the global optimal solution, $g_{\text{best}}=[g_1, g_2,\ldots\ldots, g_n]$. The second point is the optimal solution for each particle in its own experience: the individual optimal solution, $p_{\text{besti}}=[p_{i1}, p_{i2},\ldots\ldots, p_{in}]$. The ith particle is expressed by $x_i=[x_{i1}, x_{i2},\ldots\ldots, x_{in}]$, and the kth correction (particle velocity) is $v_i^k=[v_{i1}^k, v_{i2}^k,\ldots\ldots, v_{in}^k]$. The iterative formulas are as follows:

$$v_{id}^k = w_i v_{id}^{k-1} + c_1 \times rand_1 \times \left(p_{id}^{k-1} - x_{id}^{k-1}\right) + c_2 \times rand_2 \times \left(g_d^{k-1} - x_{id}^{k-1}\right) \tag{1}$$

$$x_{id}^k = x_{id}^{k-1} + v_{id}^k \tag{2}$$

where $i=1, 2,\ldots\ldots, m$ and $d=1, 2,\ldots\ldots, n$. m is the number of the particles in the swarm, n is the dimension number of the solution vectors, c_1 and c_2 are positive constants, and $rand_1$ and $rand_2$ are random numbers between zero and one. w_i is the inertia weight.

To improve the performance of particle swarm optimisation, inertia weight was adjusted according to the following equation [3]:

$$w = w_0\left(1 - \left(\frac{k-1}{k}\right)^n\right) \tag{3}$$

where w_0 is a given constant, k is the number of flights, and n is a constant.

2.2. Support Vector Machine

SVM is a machine learning tool that uses statistical learning theory to solve multi-dimensional functions. It is based on structural risk minimisation principles, which overcomes the extra-learning problem of ANN. First, it uses the linear regression function $f(x)=w\cdot x+b$ to fit data $\{x_i, y_i\}$, $i=1,\ldots, N$, $x_i\in R_d$, $y_i\in R$ and supposes that all trained data may be fitted within the tolerated precision for the linear function, ε. Using nonlinear relationships, the data samples are mapped from the original space to a higher-dimensional characteristic space: $\varphi(x_1)=(\varphi(x_1), \varphi(x_2),\ldots, \varphi(x_N))$. In the higher-dimensional space, the optimal decision function $f(x)=w\cdot\varphi(x)+b$ is constructed. Thus, the complex nonlinear estimation function becomes a linear estimation function in higher-dimensional space. The standard SVM of Vapnik [22] and least square SVM of Suykens [23] select different allowed slack variables (ξ): ξ and the two norm of ξ, respectively. For least square SVM, the optimisation problem becomes:

$$\begin{aligned} &\min J(w,\xi) = \frac{1}{2}w^T \cdot w + c\sum_{i=1}^{N} \xi_k^2 \\ &s.t: y_k = \varphi(x_k)\cdot w^T + b + \xi_k, k = 1,\cdots,N. \end{aligned} \tag{4}$$

In formula (4), ξ is the slack variable and c is the penal factor used to adjust model complexity and training error. The optimisation problem is solved by the Lagrange method:

$$\begin{aligned} &L(w,b,\xi,a) = \frac{1}{2}w^T \cdot w + \\ &c\sum_{k=1}^{N} \xi_k^2 - \sum_{k=1}^{N} a_k\left(w^T \cdot \phi(x_k) + b + \xi_k - y_k\right) \end{aligned} \tag{5}$$

where $a_k(k=1,\ldots,N$, N is an integer) are Lagrange multipliers. According to the optimisation conditions, the partial derivatives are solved for w, b, ξ, and a, and these terms are made zero, yielding:

$$\begin{aligned} &w = \sum_{k=1}^{N} a_k\phi(x_k), \sum_{k=1}^{N} a_k = 0, a_k = c\xi_k, \\ &w^T \cdot \phi(x_k) + b + \xi_k - y_k = 0 \end{aligned} \tag{6}$$

The inner product function is defined as $k(x_i,x_j)=\varphi(x_i)\cdot\varphi(x_j)$, $k(x_i,x_j)$ which is a symmetrical function matching the Mercer condition. According to Eq. (6), the optimisation problem becomes solving a system of linear equations.

$$\begin{bmatrix} 0 & 1 & \cdots & 1 \\ 1 & k(x_1,x_1) + 1/c & \cdots & k(x_1,x_1) \\ \vdots & \vdots & \ddots & \vdots \\ 1 & k(x_N,x_1) & \cdots & k(x_N,x_N) + 1/c \end{bmatrix} \begin{bmatrix} b \\ a_1 \\ \vdots \\ a_N \end{bmatrix} = \begin{bmatrix} 0 \\ y_1 \\ \vdots \\ y_N \end{bmatrix} \tag{7}$$

Finally, the nonlinear model is given as follows:

$$f(x) = \sum_{k=1}^{N} a_k k(x,x_k) + b \tag{8}$$

The system of linear equations can be solved by the least square method. The training method, called the Least Square-Support Vector Machine (LS-SVM), has a faster training speed than standard SVM. In Eq. (8), the inner product function $k(x, x_k)$ could be divided into three kernel functions: a polynomial kernel function, a Gauss kernel function and a sigmoid kernel function. The Gauss kernel function yields good calculation results due to several advantages: (1) the Gauss kernel function has better forecast performance than the Sigmoid kernel; (2) the Gauss kernel requires fewer parameters than the polynomial kernel; and (3) the Gauss kernel function is universal, so it can fit all data samples and produce smooth estimates. This study uses the Gauss kernel function of formula (9) for $k(x, x_k)$:

$$k(x,x_i) = \exp(-\frac{|x-x_i|^2}{2\sigma^2}) \tag{9}$$

where σ is a constant called the kernel parameter.

3. The tunnel feedback control method based on PSO-SVM

In this section, an intelligent displacement control algorithm is provided based on the integration of PSO, SVM and numerical analysis. The algorithm is shown in Fig. 1. The control procedure can be divided into two main sections: feedback analysis of the mechanical parameters of the surrounding rock and optimisation of the supporting scheme based on recognised rock parameters. Each section includes training the SVM model and using it to optimise parameters, as described below.

3.1. Non-linear relationship expressed by SVM

The non-linear relationship between the parameters of the rock-supporting system and the displacement of surrounding rock can be described using an SVM model, SVM(X):

$$\begin{aligned} &SVM(X):R^n \rightarrow R \\ &Y = SVM(X) \\ &X = (x_1, x_2, \cdots, x_n) \end{aligned} \tag{10}$$

where $x_i(i=1,2,\ldots,n)$ are the parameters of the rock-supporting system such as Young's modulus, shotcrete thickness, shotcrete Young's modulus, cable diameter, and cable length. Y is the displacement of the surrounding rock at the key point.

SVM(X) is obtained through a training process that includes the creation of training samples using numerical simulation and the determination of SVM training parameters. The training samples are created by applying numerical analysis to the given orthogonal experimental design to obtain the corresponding displacement of rock mass at key points. In consideration of the influence of training parameters (kernel parameter σ and penal factor c) on the generation performance of SVM, these parameters are found by particle swarm optimisation arithmetic in global space, as described below:

Step 1 For each analysis task, training data sets are constructed that correspond to the geomechanical parameters (or supporting parameters) and displacement at key points. Numerical analysis is used to calculate the data set for the every set of orthogonal experimental schemes. To improve the generation performance

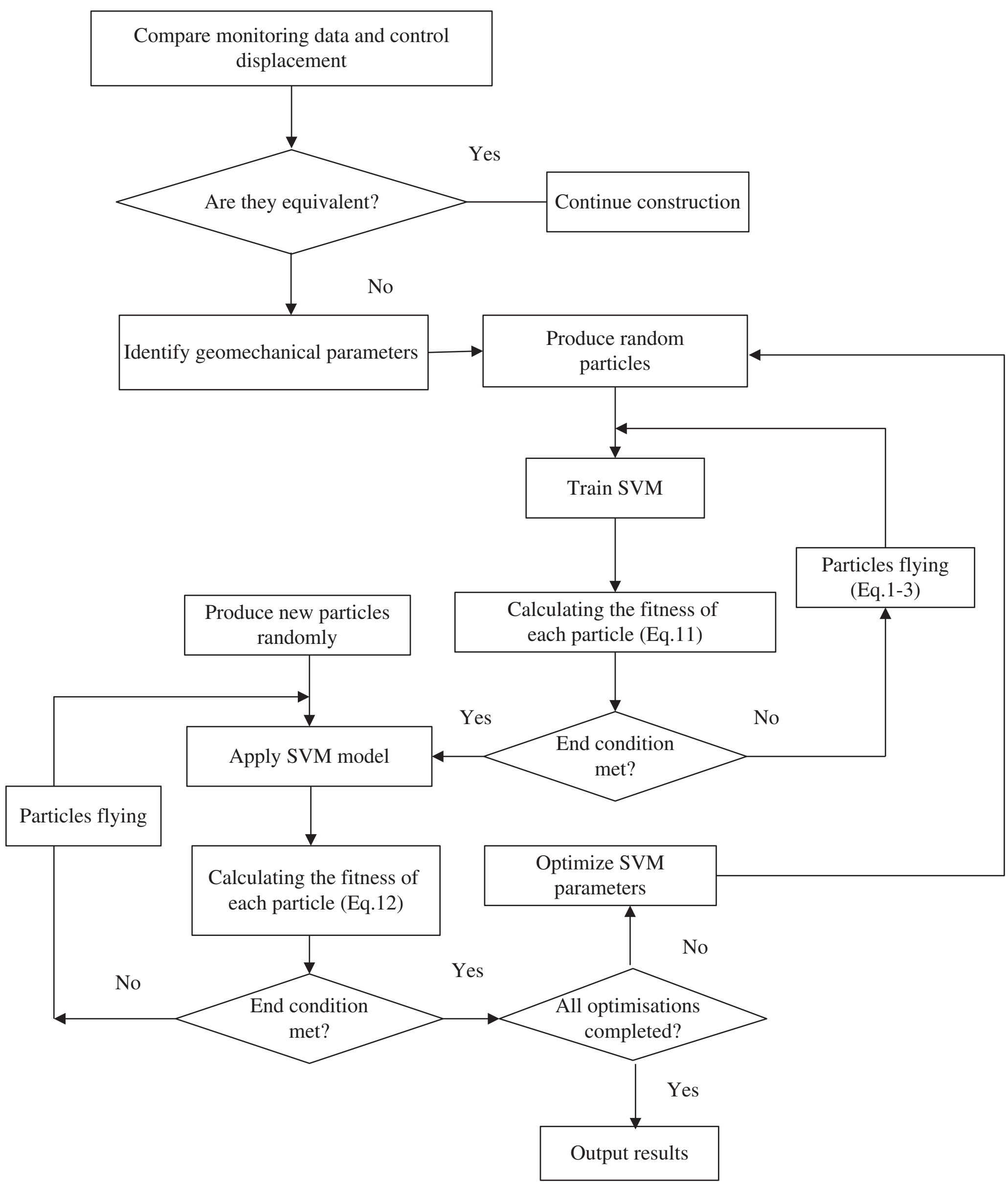

Fig. 1. Flow chart presenting the tunnel construction feedback optimisation method.

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of SVM, a testing sample set is selected from the data set and used to assess the applicability of SVM.

Step 2 The parameters of PSO-SVM are initialised, including population size, evolutionary generation number, initial value of inertia weight, and parameter ranges for σ and c of the SVM kernel function. Initial particles are produced randomly, yielding a set of c and σ values within the given ranges. Each selected kernel function with its parameters is considered an individual for SVM.

Step 3 The SVM is trained using the corresponding values of c and σ, and the predicted values are compared with test samples. The applicability of the model is measured in terms of fitness:

$$\text{Fitness} = \max\left(\left\{\frac{\left|x_j - x_j'\right|}{x_j'}\right\}, j = 1, 2, \ \ldots, k\right) \tag{11}$$

where x_j and x_j' are the estimated displacement of the tentative SVM and the calculated key point rock mass at the jth testing sample. The test number is $j = 1,2,\ldots\ldots k$, k.

Step 4 For the ith particle in the population, fitness p_i is compared with the local optimal solution p_{besti}. If $p_i < p_{\text{besti}}$, then $p_{\text{best}i}$ is replaced by p_i and x_{pbesti} equals x_i.

Step 5 Step 4 is repeated for each particle in the population, and the fitness of the optimal solution p_{besti} is compared with the fitness of global optimal solution of the former generation, g_{best}. If $p_{\text{best}i} < g_{\text{best}}$, then g_{best} is replaced by $p_{\text{best}i}$ and the corresponding particle is designated the optimal one: x_{gbest} equals x_i.

Step 6 If the fitness is accepted, the SVM training procedure ends, outputting the supporting vectors. If not, new particles are produced according to Eqs. (1)–(3), and the process returns to Step 2.

3.2. Feedback optimisation process

Both back analysis of the mechanical parameters of surrounding rock or supporting scheme optimisation can be treated as an optimisation problem and solved by PSO. The fitness function for PSO arithmetic considers the essence of parameter back analysis and supporting parameter optimisation:

$$fitness = \frac{1}{m}\sum_{i=1}^{m}\left(\left|SVM_i(X) - Y_i\right|\right) \tag{12}$$

where m is the number of key points (or measure lines) and Y_i is the monitored displacement or controlling displacement of the ith key point.

The method for tunnel displacement optimisation control based on the SVM model is as follows:

Step 1 The monitoring displacement is compared with the objective displacement. If they are equivalent, the original supporting scheme is maintained and construction is continued. If there is a significant difference between the monitoring and control displacements, the process proceeds to Step 2.

Step 2 The geomechanical parameters for identification and their ranges are selected.

Step 3 Individual n particles are randomly generated within their given ranges. Each individual represents an initial solution.

Step 4 According to Section 3.1, the SVM model is made to describe the nonlinear relation between parameters and key displacement. A set of parameters are input to the SVM obtained above to calculate the displacement of key points.

Step 5 The fitness of current individual p_i is evaluated according to Eq. (12) to determine the local optimal fitness, p_{besti}, and the local optimal solution, x_{besti}, of the individual.

Step 6 If all of the individuals are evaluated, the global optimal fitness, g_{best}, and its corresponding solution, x_{best}, are obtained for the population. Otherwise, the process repeats from Step 4.

Step 7 If demands are satisfied for the iteration number or minimal error and the optimal parameters are given, the process continues from Step 9.

Step 8 The local optimal solution and global optimal solution are obtained. Particles iterate according to Eqs. (1) and (2), and inertia weight iterates according to Eq. (3); the process repeats from Step 4.

Step 9 If the supporting parameters are optimised, the optimisation result is produced and the supporting scheme is adjusted. If only the rock mechanical parameters are optimised according to the recognised parameters, the supporting scheme parameters and their ranges are determined and the process repeats from Step 3 until the optimal supporting scheme is obtained.

4. Case study

4.1. Engineering introduction

In this section, the proposed procedure is tested by applying it to the case study of a circle arc tunnel in Dalian, China. Based on geophysical explorations, the tunnel passes through two rock strata, weathering shale and weathering limestone, between stake numbers K11 + 000 and K11 + 220. The buried depth is more than 30 meters, and the surrounding rock is III class. The rock strength is low and the weathered layer is thick. There are many faults and joints. The original ground stress is according to the self-weight stress field. The tunnel is 7.4 m wide and 6.7 m high; it was excavated by the Drilling and Blasting Method and Two-Bench Excavation. The primary support must be adopted quickly after excavation to close and protect the surrounding rock and to control the deformation of the surrounding rock. The loading ring is formed of rock and supports. The monitoring points and supports of the typical tunnel section are shown in Fig. 2.

The original support scheme adopts shotcrete with a Young's modulus of 5 GPa and a thickness of 6 mm. The bolt has a diameter of 22 mm, a length of 3 m and a space of 1.2 m. The measuring points are arranged in an interval tunnel section near the tunnel face as shown on Fig. 2. During excavation, surrounding rock displacement increased and became steady. The final monitored radial displacements of the measuring line between the two points in studied section are 8.11 mm along AB, 9.15 mm along AE, 12.5 mm along AG and 0.97 mm along EF (Fig. 2).

4.2. Identification of geomechanical parameters

According to prophase exploration data, strata 1 and strata 2 both have Young's modulus values between 0.2 and 2.0 GPa and Poisson ratios between 0.2 and 0.4. Because these elastic parameters cause the surrounding rock displacement to be more evident, they were uniformly adopted in the scope for the combined 32 samples. Numerical analysis was conducted to produce the data samples shown in Table 1. The first 26 samples were used for training and the other six samples (indicated with stars) were used for testing. Other geomechanical parameters for strata 1 are as follows: cohesiveness is 1 MPa, internal friction angle is 30°, tensile strength is 0.2 Mpa and density is 2300 kg/m^3. For strata 2, cohesiveness is 1.5 MPa, internal friction angle is 35°, tensile strength is 0.5 MPa and density is 2500 kg/m^3.

The PSO parameters were set for a population scale of 20, a maximum iteration number of 30, a variables number of 4 and an initial inertia weight of 0.35. The trained SVM identified additional parameters: $E_1 = 4E8$, $E_2 = 1.1E9$, $u_1 = 0.23$, and $u_2 = 0.29$. The calculated feedback is compared with the monitored displacement in Fig. 3. The displacements calculated from the identified parameters

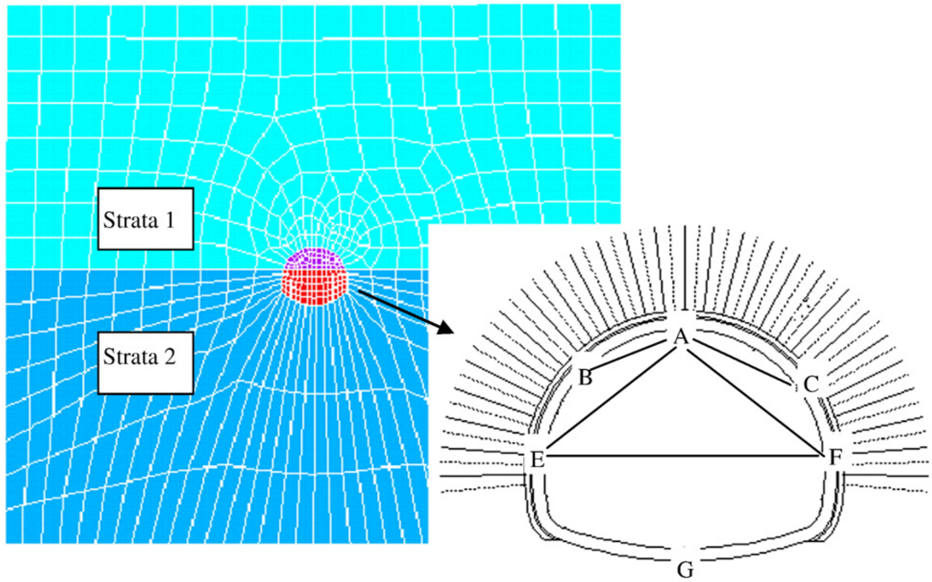

Fig. 2. Numerical grid and cross section of the tunnel.

are similar to the observed displacements from monitoring data, which demonstrates that the identified rock mechanical parameters agree well with actual conditions. The PSO convergence curve for identifying rock parameters is shown in Fig. 4, which shows that the PSO algorithm can converge quickly, and the optimal solution is therefore rapidly found. Variations of the recognised parameters are shown in Fig. 5. The mechanics parameters vacillate in the initial stage of arithmetic and tend to stabilise with further iterations, indicating progress toward the optimal parameters.

Table 1
Training and test samples used to identify rock mechanical parameters.

Scheme	E_1, GPa	μ_1	E_2, GPa	μ_2	AB, mm	AE, mm	AG, mm	EF, mm
1	0.2	0.2	0.2	0.2	16.078	20.124	37.322	2.193
2	0.2	0.27	0.7	0.27	16.013	17.567	24.259	1.187
3	0.2	0.34	1.4	0.34	16.048	16.901	20.735	2.121
4	0.2	0.4	2.0	0.4	16.093	16.593	19.028	3.202
5	0.7	0.2	0.2	0.27	4.614	7.917	22.511	2.933
6	0.7	0.27	0.7	0.2	4.440	5.759	12.387	0.434
7	0.7	0.34	1.4	0.4	4.577	4.723	6.237	2.758
8	0.7	0.4	2.0	0.34	4.528	4.758	6.954	2.552
9	1.4	0.2	0.7	0.34	2.240	2.952	6.655	1.231
10	1.4	0.27	0.2	0.4	2.418	5.152	17.476	5.009
11	1.4	0.34	2.0	0.2	2.110	2.750	6.913	0.485
12	2.0	0.2	0.7	0.4	1.596	2.060	4.6459	1.878
13	2.0	0.27	0.2	0.34	1.680	4.603	17.891	4.362
14	2.0	0.34	2.0	0.27	1.473	1.830	4.702	1.222
15	0.2	0.2	2.0	0.2	15.961	17.145	22.361	0.385
16	0.2	0.27	1.4	0.27	15.987	17.094	21.902	1.269
17	0.2	0.34	0.7	0.34	16.073	17.374	23.103	2.615
18	0.7	0.2	2.0	0.27	4.457	4.938	7.662	0.239
19	0.7	0.27	1.4	0.2	4.428	5.287	10.030	5.889
20	0.7	0.34	0.7	0.4	4.692	5.196	8.595	3.234
21	1.4	0.2	1.4	0.34	2.295	2.479	4.298	0.872
22	1.4	0.27	2.0	0.4	2.260	2.173	2.626	1.928
23	1.4	0.4	0.7	0.27	2.262	3.471	8.776	2.475
24	2.0	0.2	1.4	0.4	1.571	1.587	2.289	1.381
25	2.0	0.27	2.0	0.34	1.523	1.674	3.041	1.287
26	2.0	0.34	0.2	0.27	1.631	4.839	19.552	4.303
27*	2.0	0.4	0.7	0.2	1.457	2.656	9.393	1.790
28*	1.4	0.34	0.2	0.2	2.268	5.729	21.763	3.566
29*	0.7	0.4	0.2	0.34	4.685	7.737	21.80	5.623
30*	0.2	0.4	0.2	0.4	16.290	19.573	33.878	6.270
31*	2.0	0.4	1.4	0.2	1.432	2.177	7.035	1.218
32*	1.4	0.4	1.4	0.27	2.177	2.698	6.418	1.966

4.3. Optimisation of shotcrete parameters

Support parameters like bolt and shotcrete specifications can be adjusted to control tunnel displacement. In this case, the bolts parameters are not changed from the original scheme, and the shotcrete parameters (layer thickness and layer Young's modulus) are adjusted to

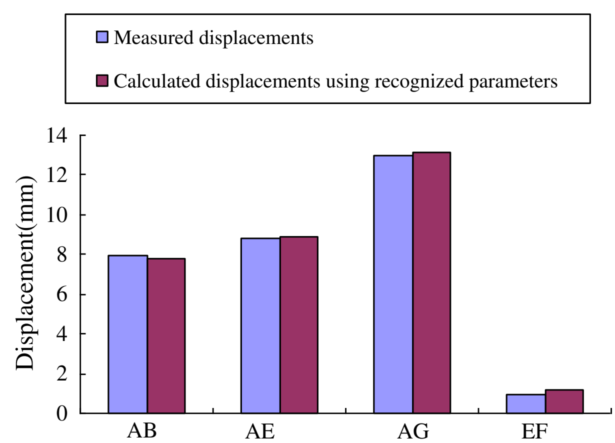

Fig. 3. Comparison of feedback-analysed and measured displacements.

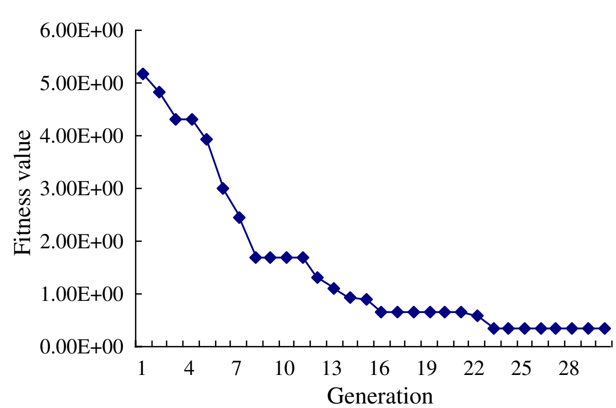

Fig. 4. Fitness values by generation.

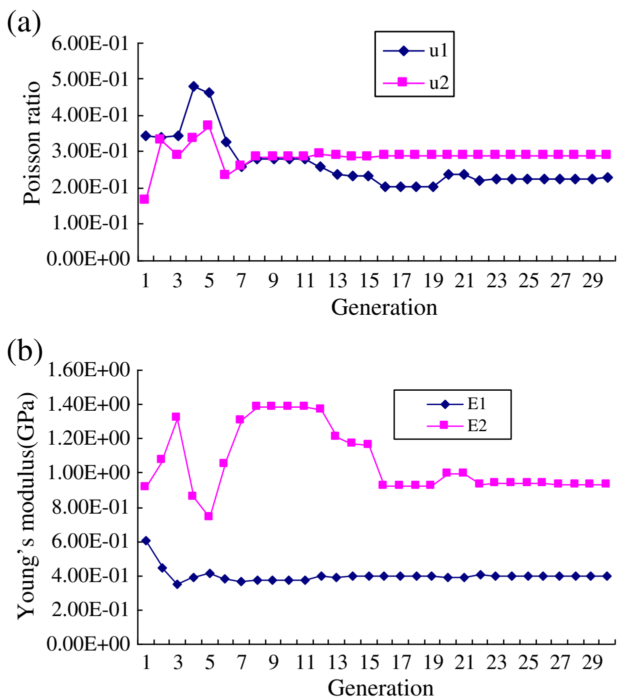

Fig. 5. Variation of the recognised parameters (E_1,E_2,u_1 and u_2).

Table 2
Training and test samples used to optimise shotcrete parameters.

Scheme	Thickness, cm	Elastic modulus, GPa	AG, mm	Scheme	Thickness, cm	Elastic modulus, GPa	AG, mm
1	6	5	12.5	9	6	30	9.1
2	12	10	10.1	10	12	50	6.7
3	18	30	6.8	11	18	5	10.8
4	24	50	5.7	12	24	10	8.4
5	6	10	11.7	13	6	50	7.9
6	12	30	7.6	14*	12	5	11.7
7	18	50	6.1	15*	18	10	9.1
8	24	5	10.1	16*	24	30	6.3

control the surrounding rock displacement along AG. Shotcrete parameters and displacements for the 16 samples obtained by numerical analysis prior to training the SVM are shown in Table 2; the first 13 samples were used for training, and the other three samples (indicated with stars) were used for testing.

Using data from Table 2, the SVM model was trained by substituting 7 mm AG for the control objective in formula (12). The variables number was set to 2, the population scale was 40, the iteration number was 60 and the initial inertia weight was 0.35. The PSO-optimised shotcrete parameters were 11.85 mm thickness (which can be 12 mm according to a simple rounding approach for construction) and a Young's modulus of 21.45 GPa. The result of a numerical analysis based on only optimised parameters is shown in Fig. 6. The displacement of arc subsidence is about 5 mm, the bottom rising displacement is about 2 mm, and the convergence displacement of AG is about 7 mm.

Fig. 7a shows the fitness values of first generation particles in the PSO searching process. The values are large and dispersed because randomly produced particles in the prescribed range are far from the optimal solution. Fig. 7b shows the fifth generation particles for which the values of whole particle fitness are obviously reduced. Fig. 7c shows the 20th generation particles, which have more depressed fitness values and are divided into two parts that approach 1.5 and 0. Fig. 7d shows particles of the 60th generation; the fitness values for this generation more strongly approach zero.

The PSO fitness values for searched shotcrete thickness and shotcrete Young's modulus by iteration are shown in Fig. 8. This figure shows that fitness values for the initial stage are large and that the particles are far from the optimal solution. With additional rounds of iteration, the particles approach the optimal solution and the corresponding fitness values decrease. The optimal solution is achieved after the 20th round. This also demonstrates the good convergence of the PSO algorithm.

5. Discussion

In the above optimisation process, the kernel parameter σ and the penal coefficient c are important factors that affect the generational performance of SVM. Effects of SVM parameters on the forecast result are shown in Figs. 9 and 10. In these figures, longitudinal coordinates represents relative error, which is defined as the ratio of the absolute measuring error to the true value. The horizontal coordinates in Figs. 9

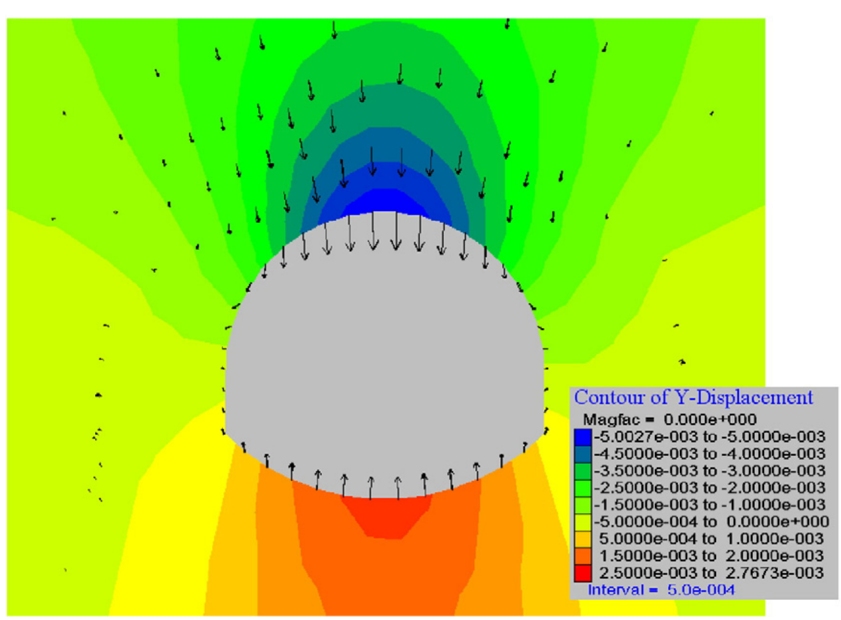

Fig. 6. Contour diagram of the vertical displacement from numerical analysis.

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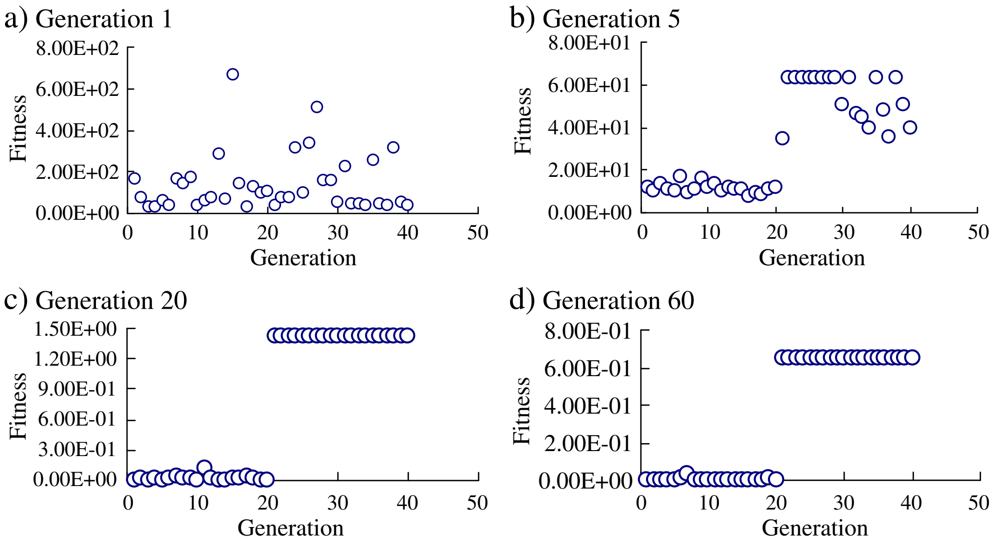

Fig. 7. Fitness values by generation.

and 10 are the penal factor, c, and the kernel parameter, σ, respectively. For values of c below 20, the magnitude of the forecast error of SVM approaches 0.6; when c increases to more than 20, the forecast error of SVM is reduced to 0.05. When σ is less than one or more than two, the magnitude of the corresponding forecast error is more than 0.1 and when σ is between one and two, the corresponding forecast error is reduced to 0.04. Variations in the penal factor, c, and the kernel parameter, σ, will change the SVM forecast error, which shows that it is imperative to select proper parameters to guarantee the forecast performance of SVM. Because SVM is not a method for selecting these parameters, optimising SVM parameters through PSO arithmetic can avoid blind parameter selection. The convergence of the PSO search for the SVM parameters is shown in Fig. 11. Smaller fitness values permit the generation of better solutions by arithmetic. Fig. 11 shows that an iteration number of 6 is associated with a fitness value as low as 0.05. This demonstrates that PSO is capable of rapidly identifying optimal parameters of SVM.

In the tunnel construction process, the tunnel design should control the surrounding displacement to get clearance within a section. If the displacement of the surrounding rock is too small, an excessively large supporting force is needed. However, if displacement exceeds the allowable value, the stability of the surrounding rock cannot be guaranteed. Therefore, a suitable convergence displacement of the surrounding rock is needed, which is referred to as objective displacement in this paper. Objective displacement should be determined by the properties of the surrounding rock, cavern size and buried

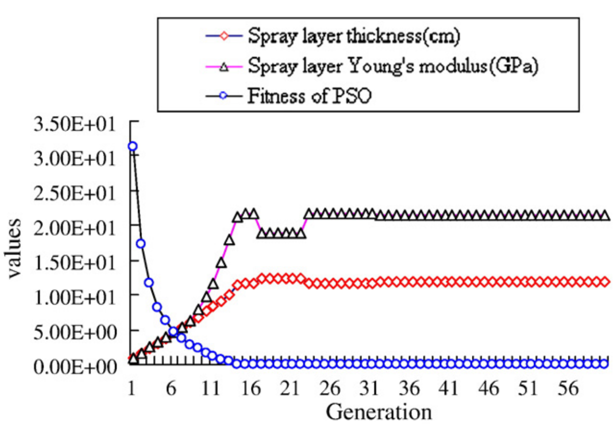

Fig. 8. Variations in parameters and fitness by generation.

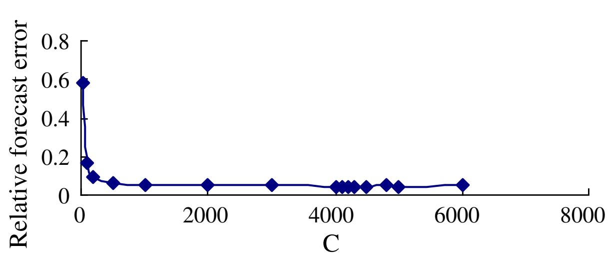

Fig. 9. Relationship between relative SVM forecast error and parameter c.

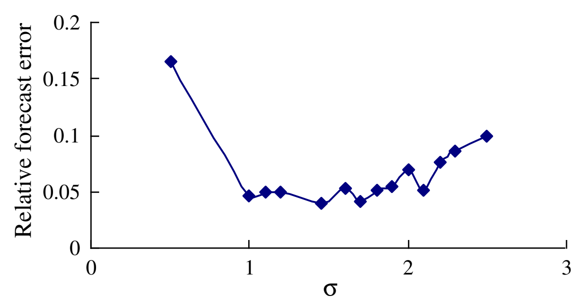

Fig. 10. Relationship between relative SVM forecast error and parameter σ.

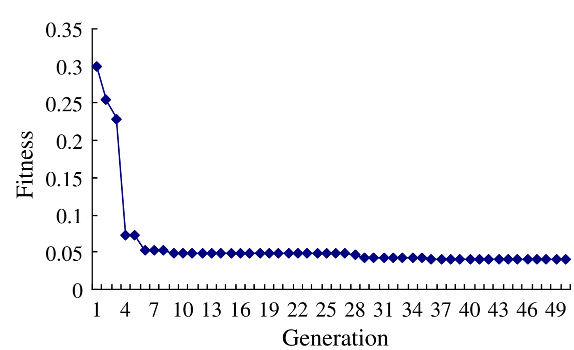

Fig. 11. Minimum SVM fitness by generation.

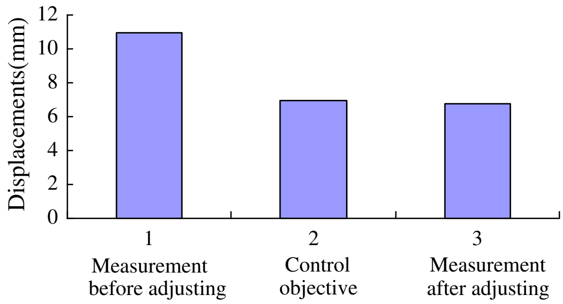

Fig. 12. Measured AG displacement and the control objective.

depth of the tunnel. The observed AG displacement is 11 mm, which corresponds to an original shotcrete support scheme with a Young's modulus of 5 GPa and a thickness of 6 mm. The control objective of AG is 7 mm. Based on the control method proposed here, the feedback-optimised shotcrete has a thickness of 12 mm, a Young's modulus of 21.45 GPa and a corresponding displacement along AG of 7.2 mm (Fig. 12). The optimised parameters provide an acceptable control for the displacement objective.

The suggested method is based on conceptual feedback and optimisation designs for tunnel construction. Rock mechanical parameters and support parameters represent system inputs, and the surrounding rock displacements are the system outputs. Numerical analysis, support vector machine and particle swarm optimisation are effectively combined to express the system, which is capable of obtaining quantitative results for both the rock mechanical parameters and support parameters based on monitored and control objective displacements.

6. Conclusion

This study presents a feedback optimisation method based on PSO-SVM for controlling displacements during tunnel construction. It can be divided into two main sections: feedback analysis of the surrounding rock mechanical parameters and optimisation of support parameters. Feedback analysis identified characteristics of the surrounding rock, and support optimisation defines the appropriate support scheme to deform the surrounding rock according to the control objective. Both of these sections are essentially optimisation problems and include both training the SVM model and optimising the parameters based on that trained model.

Representative samples for SVM training and factor sensitivity analysis were given by the orthogonal experimental design method, which efficiently reduced the number of numerical simulations. It demonstrated that the SVM model was capable of accurately describing the nonlinear relations between displacement and rock parameters. The forecast error of SVM varied with the SVM parameters, which showed that PSO optimisation of the SVM parameters is necessary. PSO demonstrated good global optimisation performance and quick identification of optimal results. The proposed method combined the advantages of orthogonal experimental design, numerical simulation, SVM and PSO and provides a real time, quantitative and powerful means to inform construction activities and adjust dynamic construction schemes. The case study demonstrated that the displacements predicted by the identified parameters were in good agreement with field measurements and that the obtained shotcrete parameters were an acceptable control for the deform of surrounding rock.

In this research, the method is applied only to the control of the displacement objective and optimisation of the shotcrete parameters. Future research should be conducted to improve the flexibility of the method by applying it to additional objectives for economics, damage zones and other support parameters such as cable design.

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