HYBRID MODEL FOR DISPLACEMENT PREDICTION OF TUNNEL SURROUNDING ROCK

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Abstract: This paper presents a hybrid method to predict tunnel surrounding rock displacement, which is one of the most important factors for quality control and safety during tunnel construction. The hybrid method comprises two phases, one is support vector machine (SVM)-based model for predicting the tunnel surrounding rock displacement, and the other is GA-based model for optimizing the parameters in the SVM. The proposed model is evaluated with the data of tunnel surrounding rock displacement on the tunnel of Wuhan-Guangzhou railway in China. The results show that genetic algorithm (GA) has a good convergence and relative stable performance. The comparison results also show that the hybrid method can generally provide a better performance than artificial neural network (ANN) and finite element method (FEM) for tunnel surrounding rock displacement prediction.

Key words: *Prediction, tunnel, surrounding rock displacement, SVM, GA*

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1. Introduction

Many cities of China are experiencing a rapid development in subway, railway and other infrastructure, in which tunnel construction may be involved in some cases. Tunnel construction is always accompanied by a very large cost. Quality control and safety during tunnel construction represent increasingly important concerns. It is very important how to perceive the potential danger in a timely and accurate way for successful tunnel construction. Recently, some works on analysis of tunnel

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surrounding rock have appeared. Li *et al.* (2005) presented grey majorized model to predict the displacement of tunnel surrounding rock; this model was based on the simulation and prediction of equidistant, non-equidistant and high growth data sequent. Aydan *et al.* (1993; 1996) firstly analyzed the associated factors and the mechanism of squeezing rock of tunnels. Then, they presented a practical method based on the time-dependent behavior of squeezing rock to predict the squeezing potential and deformation of tunnels in squeezing rock. Hoek and Marinos (2000) predicted tunnel squeezing problems in weak heterogeneous rock masses by estimating the strength and deformation properties of weak heterogeneous rock masses. Barla and Borgna (2000) analyzed the rock mass response during tunnel excavation and presented numerical methods to simulate the behavior of different models for the rock mass. Sunuwar and Fowell (2001) presented a method to predict the rock squeezing problem in different tunnels of hydropower projects, which indicated that squeezing ground conditions were greatly influenced by some factors. Tunnel surrounding rock displacement is one of the most important parameters for quality control and safety. This paper focuses on the prediction of tunnel surrounding rock displacement. To the best of our knowledge, there are only a few works dealing with this problem.

Since there are some stochastic factors (such as temperatures, early age concrete shrinkage and creep) during tunnel construction, it is very difficult to predict the displacement of tunnel surrounding rock. Recently, support vector machines (SVMs) have been proposed as a novel technique for classification and regression (Vapnik, 1999). SVM shows very resistant to the overfitting problem, achieving high generalization performance in solving various time series forecasting problems, which has been applied in prediction of time series (Cao and Tay, 2003). These successful applications motivate us to apply SVM in the displacement prediction of tunnel surrounding rock.

The parameters in SVM, which greatly influence the performance of SVM, need to be optimized and set by users. As identifying the parameters in SVM, grid-search (Hsu *et al*, 2003; Yu *et al.*, 2009; 2011) is the most reliable method when the search time is not considered. However, for large scale or real-time feature practice application, the considerable search time cannot be accepted. Heuristic algorithms have been successfully used in many complex problems (Yu *et al.*, 2011; 2012). Many studies have been devoted to improving the efficiency of the parameter optimization in SVM by using heuristic algorithms. Lin *et al.* (2006) introduced a structural risk minimization principle to determine appropriate parameters in the SVM prediction model. In order to identify appropriate parameters in the SVM prediction model, a new kernel function is presented by Ohn *et al.* (2004). Lorena *et al.* (2008) used genetic algorithms to produce a set of parameter values for tuning the parameters in SVM. Lin *et al.* (2008) proposed a particle swarm optimization to optimize the parameters in SVM. Hou and Li (2009) presented evolution strategy with covariance matrix adaptation to identify the parameters in SVM. The paper attempts to find the appropriate parameters in SVM by using genetic algorithms which we use as a search technique and which has been successfully applied in various optimization problems (Dong *et al.* 2005; Pai, 2006).

This paper presents a hybrid prediction model based on SVM and genetic algorithm (GA) for tunnel surrounding rock displacement, which is called SVM-GA. The remainder of the paper is organized as follows. In Section 2, we provide the structure of the hybrid model for predicting tunnel surrounding rock displacement, and a brief introduction about a prediction model on SVM and parameters optimization on GA are presented. In Section 3, computational results are discussed; and finally, the conclusions are provided in Section 4.

2. Model Developments

The hybrid model consists of two phases: one is an SVM-based model for prediction of the tunnel surrounding rock displacement; the other is a GA-based model for optimization of the parameters in SVM. The prediction model can be described as in Fig. 1. Then, two sub-models are discussed, respectively.

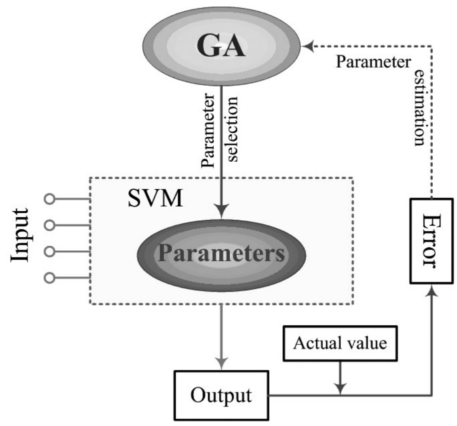

Fig. 1 *The framework of the hybrid model.*

2.1 SVM-GA for tunnel surrounding rock displacement prediction

SVM is a learning technique which is based on the structural risk minimization principle to minimize an upper bound of generalization error. By applying a set of high dimensional linear functions, SVM is shown to have high generalization ability, and so it can more easily capture reliability data patterns than other the models.

2.1.1 SVM for regression

Given the training data set $\{x_k, y_k\}, k = 1, 2, \ldots, s, x_k \in R^m, y_k \in R^n$, k is the number of training samples. These points are randomly and independently generated from an unknown function. SVM estimates the function by the following function:

$$f(x) =< w, x > +b, \qquad w, x \in R^m, b \in R^n, \tag{1}$$

where $< w, x >$ is the feature of the inputs. The coefficients w and b are estimated by the so-called regularized risk functional:

$$MinJ = \frac{1}{2} \|w\|^2 + C \cdot R_{emp}[f]. \tag{2}$$

The first term $\frac{1}{2} \|w\|^2$ is called the regularized term which is used as a measurement of function flatness. The second term $R_{emp}[f]$ is the so-called loss function for measuring the empirical error. C is regularization constant to determine the trade-off between the training error and the generalization performance. Here, we use the ε-insensitive loss function to measure empirical error:

$$|y - f(x)|_{\varepsilon} = \max\{0, |y - f(x)| - \varepsilon\} \tag{3}$$

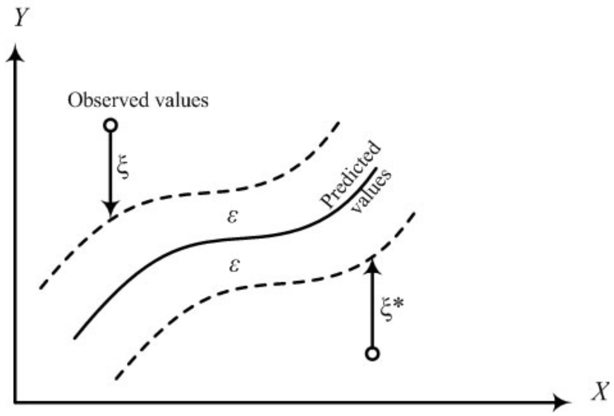

Fig. 2 *The parameters for the support vector regression.*

This defines a ε tube (Fig. 2). The loss is zero if the predicted value is within the tube. If the predicted point is outside the tube, the loss is the magnitude of the difference between the predicted value and the radius ε of the tube. Both C and ε are user-determined parameters. Two positive slack variables ξ, ξ^* are used to cope with infeasible constraints of the optimization problem. To get the estimation of w and b, the Eq. (2) can be transformed to a primal objective function (4).

$$MinJ = \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{s} (\xi_i^* + \xi_i) \tag{4}$$

$$s.t. \begin{cases} y_i - < w, x_i > -b \leq \varepsilon + \xi_i^* \\ < w, x_i > +b - y_i \leq \varepsilon + \xi_i \\ \xi_i^*, \xi_i \geq 0 \end{cases}$$

This constrained optimization problem is solved using the following primal Lagrangian form:

$$L = \frac{1}{2}\left\|w\right\|^2 + C\sum_{i=1}^{s}(\xi_i^* + \xi_i) - \sum_{i=1}^{s}(\eta_i\xi_i + \eta_i^*\xi_i^*) - \sum_{i=1}^{s}\alpha_i(\varepsilon + \xi_i - y_i + \langle w, x_i\rangle + b) - \sum_{i=1}^{s}\alpha_i^*(\varepsilon + \xi^* - y_i + \langle w, x_i\rangle + b), \tag{5}$$

where L is the Lagrangian and η_i, η_i^*, α_i, α_i^* are Lagrange multipliers. Hence the dual variables in (5) have to satisfy the positive constraints.

$$\eta_i, \eta_i^*, \alpha_i, \alpha_i^* \geq 0 \tag{6}$$

The above problem can be converted into a dual problem where the task is to optimize the Lagrangian multipliers, α_i and α_i^*. The dual problem contains a quadratic objective function of α_i and α_i^* with one linear constraint:

$$MaxJ = -\frac{1}{2}\sum_{i,j=1}^{s}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j) < x_i, x_j > + \sum_{i=1}^{s}\alpha_i^*(y_i - \varepsilon) - \sum_{i=1}^{s}\alpha_i(y_i + \varepsilon) \tag{7}$$

$$s.t. \begin{cases} \sum_{i=1}^{s}\alpha_i = \sum_{i=1}^{s}\alpha_i^* \\ 0 \leq \alpha_i \leq C \\ 0 \leq \alpha_i^* \leq C \end{cases}$$

Let

$$w = \sum_{i=1}^{s}(\alpha_i - \alpha_i^*)x_i \tag{8}$$

Thus,

$$f(x) = \sum_{i=1}^{s}(\alpha_i - \alpha_i^*) < x_i, x_j > + b \tag{9}$$

By introducing kernel function $K(x_i x_j)$ the Eq. (8) can be rewritten as follows:

$$f(x) = \sum_{i=1}^{s}(\alpha_i - \alpha_i^*)K(x_i, x_j) + b, \tag{10}$$

where $K(x_i, x_j)$ is the so-called kernel function, which is proven to simplify the use of mapping. The value of $K(x_i x_j)$ is equal to the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$, that is, $K(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$. By the use of kernels, all necessary computations can be performed directly in input space, without having to compute the map $\phi(x)$. More details can be seen in (Vapnik, 1999; Cao, 2003).

2.1.2 Applying SVM in tunnel surrounding rock displacement prediction

The estimation of tunnel surrounding rock displacement is a difficult task due to some stochastic factors. Furthermore, tunnel surrounding rock displacement has become one of the most important parameters for quality control and safety. It is obvious that the tunnel surrounding rock displacement is highly related with the conditions of rock. Therefore, it is appropriate to use the historical surrounding rock displacements to estimate the future displacements. The prediction model for surrounding rock displacements focuses on generalizing the relationship of the following equation:

$$\hat{D}(t) = f[d(t-1), d(t-2), ..., d(t-n)], \tag{11}$$

where $\hat{D}(t)$ denotes the estimated surrounding rock displacements of the t^{th} data, and $d(t\text{-}1)$ denotes the surrounding rock displacements of the $(t\text{-}1)^{\text{th}}$ data.

In general, the parameter n will induce different prediction effect. At first, the displacement changes obviously, and the value of n will greatly affect the prediction accuracy. As time goes by, the surrounding rock is becoming stable gradually and the effect of n turns smaller correspondingly. In this paper, we want to determine the suitable value for the first stage. Thus, we adopt a simulation approach with the use of historical data. From the result of the simulation, it can be found out that lengthening or reducing the number of preceding data cannot improve the prediction accuracy, and it can be also observed that the prediction accuracy is the best while the number of data is equal to 4. This can be due to the fact that the preceding data can reflect the following data. However, since the conditions vary during tunnel construction, it will diminish the effect of the very old data. Therefore, in this paper, we apply the displacement of the first four data sets to predict the displacement of the 5^{th} data set. Then the data (from the 2^{nd} data set to the 5^{th} data set) are used as input to predict the 6^{th} data set. The rest can be done in the same manner.

2.2 GA for parameter optimization

Thus, SVM is feasible and applicable in predicting the tunnel surrounding rock displacement. However, the ability of SVM mainly depends on the kernel function. In general, the RBF kernel, as a nonlinearly kernel function, is a reasonable first choice (Dong *et al.*, 2005). The parameters C, ε and σ, are the key elements of the RBF kernel and they directly decide about the prediction performance of SVM. So the parameter optimization is an important factor for improving the prediction accuracy of SVM. GA is applied to optimize the parameters in SVM.

GA is inspired by evolutionary biology like inheritance, selection, crossover, and mutation. Based on a fitness function, GA attempts to retain relatively good genetic information from generation to generation. The process of GA can be briefly described as follows:

Encoding of chromosome In GA, solution is firstly represented by a chromosome that is composed of "genes". For parameter optimizations in SVM, the real encodings were adopted since the parameters C, ε and σ are continuous-valued. To represent the parameters in SVM, thus, each chromosome consists of gen_1^t, gen_2^t and gen_3^t, which represent three parameters, respectively. Here t is the current generation. To reduce the search spacereferring to previous literature using SVM, it is recommended to the constraints of the three parameters which respectively attribute to the range $C \in [2^{-5}, 2^{5}]$, $\varepsilon \in [2^{-13}, 2^{-1}]$, and $\sigma \in [0, 2]$. An example of encoding of chromosome is shown in Fig 3

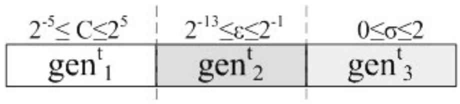

Fig. 3 *An example of chromosome encoding.*

where $2^{-5} \leq gen_1^t \leq 2^5$, $2^{-13} \leq gen_2^t \leq 2^{-1}$, $0 \leq gen_3^t \leq 2$.

Fitness function Fitness function determines possible solutions to the problem and is used to estimate the quality of the represented solution (chromosome). For parameter optimizations in SVM, the best solution is able to minimize the error of prediction. Generally, GA is an optimal searching method to find the maximum fitness of the individual chromosome. Thus, negative root mean squared error (NRMSE), which is used in literature (Dong *et al.*, 2005), is also adopted in this paper.

$$fit = -\left[\frac{\sum_{i=1}^{n}(V - \hat{V})}{n - p}\right]^{1/2}, \tag{12}$$

where $\hat{V}$ is the prediction value by the model; V is the observed value; n is the number of observations, and p is the number of model parameters.

Crossover operation Crossover is a reproduction operation in GA, which is used to vary the programming from one generation to the next by exchanging genetic information between parent chromosomes.

In the paper, an arithmetic crossover (Yu *et al.*, 2007) is used to create new offspring.

$$\begin{aligned} gen_{k,I}^{t} &= \alpha_i gen_{k,I}^{t-1} + (1 - \alpha_k) gen_{k,II}^{t-1} \\ gen_{k,II}^{t} &= \alpha_i gen_{k,II}^{t-1} + (1 - \alpha_k) gen_{k,I}^{t-1} \end{aligned}, \tag{13}$$

where $gen_{k,I}^{t-1}$, $gen_{k,II}^{t-1}$ is a pair of "parent" chromosomes; $gen_{k,I}^{t}$, $gen_{k,II}^{t}$ is a pair of "children" chromosomes; α_k is a random number between (0,1); $k \in [1, 2, 3]$ (k is the total genes for the crossover operation).

For example, Fig. 4 shows the parents selected for crossover. When k = 1, $\alpha_k = 0.2$, the children can be seen in Fig. 5 after crossover.

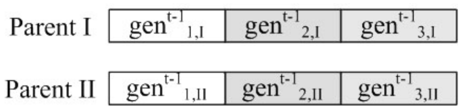

Fig. 4 *Parent chromosomes before crossover.*

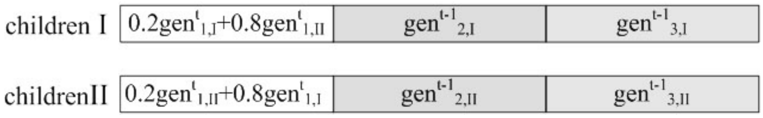

Fig. 5 *Children chromosomes after crossover.*

Mutation operation Mutation is also a reproduction operation in GA, which is used to maintain genetic diversity during evolution. A genetic mutation operation is used in this paper.

Assume a chromosome is $G = (gen_1^t, gen_2^t, gen_3^t)$, if the gen_2^t was selected for the mutation, the mutation can be shown in (14).

$$\begin{aligned} &G' = (gen_1^{t-1}, gen_2^t, gen_3^{t-1}) \\ &gen_2^t = \begin{cases} gen_2^{t-1} + \Delta(t, gen_{2\max}^t - gen_2^{t-1}) & if \quad random(0,1) = 0 \\ gen_2^{t-1} + \Delta(t, gen_2^{t-1} - gen_{2\min}^t) & if \quad random(0,1) = 1 \end{cases} . \end{aligned} \tag{14}$$

The function $\Delta(t, y)$ returns a value between [0,y] given in (15).

$$\Delta(t, y) = y \times (1 - r^{(1-t/\mathrm{T}_{\max})^{\lambda}}), \tag{15}$$

where r is a random number between [0,1]; $T_{\max}$ is the maximum number of generations; and here $\lambda = 3$. This feature causes this operation to do a uniform search in the initial space when t is small, and a very local one in later stages.

Since the genes from the mutation operations may violate the parameters constraints, there are two approaches to deal with this situation. One is to assign a relatively high weight to reduce their probability of being selected in the following search. The other one is that the solution can remain but the value needs to be adjusted to the constraints. The advantage of the second approach over the first one is that it can maintain the solution which may enable GA to investigate further points in the search space. Therefore, the second approach is adopted to deal with the chromosome which violates the constraints of parameters. The chromosome will be re-assigned a random value which meets the parameters constraints.

Termination In this paper, the search continues until RMSE_n-$\mathrm{RMSE}_{n-1} < 0.0001$ or the number of generation reaches the maximum number of generations $T_{\max}$.

3. Case Study

An experiment has been carried out to test the performance of the presented model. The Majiachong tunnel of the Wuhan-Guangzhou railway, which is a high-speed rail line between Wuhan city and Guangzhou city in China, is considered as the test bed in this study. The length of the tunnel is about 133 m and its location is from DK1692+935 to DK1693+068 of the Wuhan-Guangzhou railway. We have chosen three sections, which are uniformly distributed throughout the tunnel, to acquire the data on the tunnel surrounding rock displacement.

The embedded depth of tunnel is light and the surrounding rock of this section is soft rock belonging to V class of surrounding rock. The measurement distance on the tunnel surrounding rock displacement is mainly based on the rock classification, the tunnel section size and the embedded depth. The measurement frequency is determined by the displacement rate and the distance to the working face. In this paper, the main characteristics of the measurement distance and measurement frequency can be seen in Tab. I and Tab. II respectively.

Rock classification	Measurement distance (m)
V (shallow buried)	10∼15
V (deep buried)	20∼30
IV (shallow buried)	10∼15
IV (deep buried)	20∼30
III	40∼50
II	50∼100

Tab. I *Longitudinal pacing of measurement points.*

displacement rate (mm/d)	distance to working face (m)	measurement frequency
≥5	(0∼1)B	2∼4 times /day
1∼5	(1∼2)B	2 times /day
0.5∼1	(1∼2)B	1∼2 times /day
0.2∼0.5	(2∼5)B	1 times /day
< 0.2	> 5B	2 times /week

note B: excavation span of the tunnel

Tab. II *Frequency of measurement on crown subsidence and horizontal convergence.*

The measurement frequency is generally based on the tunnel background. For example, it can be more in special cases (Schubert *et al.*, 2002). Since the surrounding rock around the three sections is the soft rock belonging to class V (Singh and Goel, 1999), the measurement frequency is twice a day in the initial seven days. Then the frequency is once after the seventh day. The experiment continues until the tunnel surrounding rock displacement is almost stable (e.g. the difference of two consecutive measurement <0.1 mm). The date of data collection is June 22 to July 30, 2007.

3.1 Parameter identification

In our experiment, there are 138 samples in total. The data is divided into three subsets, which represent training samples, testing samples and inspection samples respectively. There are about 70% samples for training, 70% samples for testing and the remaining samples for inspection.

To properly optimize the three parameters C, ε and σ for SVM, GA is used. Before the implementation of GA, four GA parameters, namely p_c, p_m, p_{size} and T_{max}, need to be predetermined. In general, p_c varies from 0.3 to 0.9, p_m varies from 0.01 to 0.1, p_{size} is the population size which is set according to the size of the samples. T_{max} is the maximum number of generations which can be determined according to a good convergence of the calculation (Yu *et al.*, 2012). Considering the features of this problem and our experiences in GA, the characteristic of GA can be acquired, as can be seen in Tab. III. Then, GA continues running 10 times under the same condition. Fig. 6 shows the convergence of the calculation. It can be observed that the prediction error decreases fast before the 4,000th generation, and then it changes smoothly. The least prediction error appears in about the 5,000th generation, and it almost remains unchanged. Further analysis found the differences between the results from the 10 times change little. This means that GA has a good convergence. The calculation with the minimum testing NRMSE value is chosen as the most appropriate parameters in this example. Tab. IV provides prediction results and the parameters of SVM model. At last, the three parameters were optimized as (6.1263, 0.0018, and 1.3011) with the best optimization value among the 10 results for the practical prediction model of the tunnel surrounding rock displacement SVM-GA.

Parameter	(p_c)	(P_m)	(P_{size})	(T_{max})
value	0.6	0.05	80	5000

Tab. III *The characteristic of GA.*

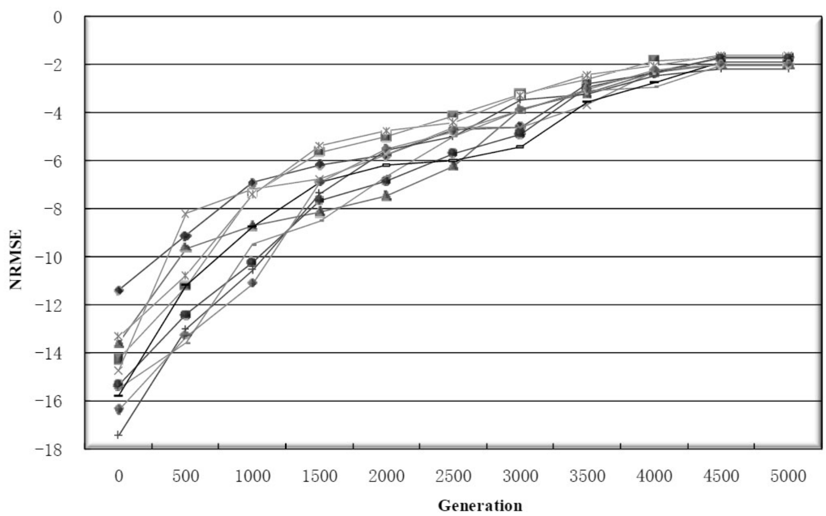

Fig. 6 *Fitness of each calculation by GA.*

Number of calculation	Parameters			Testing NRMSE
	C	ε	σ	
1	84.63	0.0008	0.7297	-1.700822944
2	177.41	0.004	0.4581	-1.693469975
3	49.32	0.00064	0.2556	-2.006978326
4	0.231	0.0128	1.5372	-1.761244713
5	13.6	0.0032	1.4213	-1.72546207
6	**6.1263**	**0.0018**	**1.3011**	**-1.614026132**
7	0.054	0.0256	0.5114	-2.174146668
8	2.261	0.0512	0.851	-2.024489722
9	5.02	0.048	1.1369	-1.89456351
10	22.96	0.02	1.3845	-1.972954724

Tab. IV *Prediction results and the parameters of SVM model.*

3.2 Results

After parameters C, ε and σ are selected, the final SVM-GA is confirmed. Then, to evaluate the performance of the proposed model, a standard Artificial Neural Network (ANN) with three-layer and Finite Element Method (FEM) were introduced using the same input data as SVM-GA. A scaled conjugate gradient algorithm (Moller, 1993) is employed for training, and the hidden neurons are optimized by trial and error. The final ANN architecture consists of five hidden neurons. Then, we compare the performance of the SVM-GA, ANN and FEM. From the results it is obvious that the RMSE values of FEM models were the largest among the three models. The RMSE of FEM is 18.21, 17.83 and 18.54 on three sections respectively. It can be explained in such a way that the FEM is a numerical technique for finding approximate solutions. It does not consider the effect of the errors in the input data, which may lead to larger MAPE values. Then, we further compare the performance of the SVM with the ANN, as can be seen in Fig. 7. From Fig. 7, it can be found out that the SVM models generally provide better tunnel surrounding rock displacement prediction. This can be attributed to the fact that SVM uses the structural risk minimization principle to minimize the generalization error, while ANN uses the empirical risk minimization principle to minimize the training error. In addition, SVM may find the global solution while ANN may tend to fall into a local optimal solution. If the parameters are properly selected, SVM may avoid over-fitting. So SVM is feasible and applicable for tunnel surrounding rock displacement prediction.

4. Conclusions

One of the most important phases during tunnel construction is to perceive the potential danger occasions such as collapse accidents as possible. Displacement prediction of tunnel surrounding rock can indirectly estimate the situation of tunnel construction. Due to the complexity of the environment in tunnel construction, this

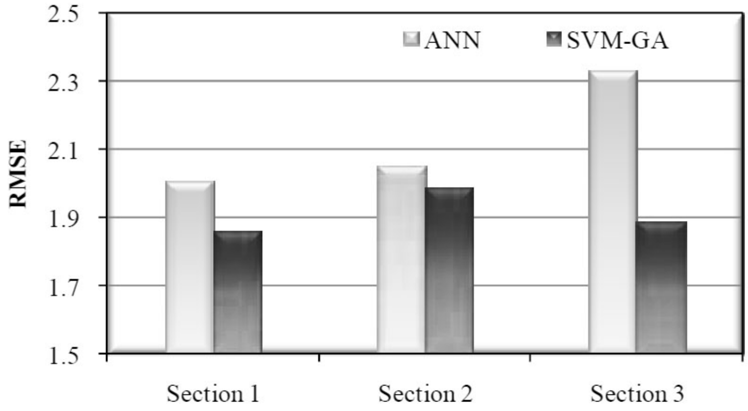

Fig. 7 *The comparison between SVM-GA and ANN.*

paper attempts to develop a hybrid model based on SVM and GA to predict the tunnel surrounding rock displacement. To evaluate the performance of the proposed method, an experiment on a tunnel of the Wuhan-Guangzhou railway is carried out. The results show that GA has a good convergence and relative stable performance. Furthermore, the comparison of results of the proposed method, ANN and FEM suggest that the SVM-GA provides lower prediction errors than the ones of the other approaches. This indicates that SVM-GA seems to be a powerful tool for tunnel surrounding rock displacement prediction.

Acknowledgments

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