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Predictive study on tunnel deformation based on LSSVM optimized by FOA

JUN LI[1,2], ZONGLIN WANG[1]

Abstract. As there are problems such as low precision and the failure of self-adaptive selection of parameters in prediction of tunnel deformation by using LSSVM, a prediction model of tunnel deformation based on Least squares support vector machine (LSSVM) optimized by FOA is proposed according to the advantages of global optimum and rapid convergence of the Fruit Flying Optimization Algorithm (FOA). The predictive study on tunnel deformation can be achieved through self-adaptive optimization of the penalty factor C and kernel function parameter g of LSSVM model. A tunnel of Guiyang-Guangzhou High-speed Rail was used as the object of study. The observation data of tunnel deformation from January 2009 to January 2015 was used as the object of study and predictive study on tunnel deformation was carried out by means of rolling prediction. As shown in the experimental result, according to the evaluation indexes of prediction time and the mean squared error of prediction (MSEP), FOA-LSSVM has higher prediction accuracy than LSSVM and BP; thus, the validity and reliability of predicting the tunnel deformation with FOA-LSSVM is verified.

Key words. FOA, LSSVM, tunnel deformation prediction, prediction accuracy, evaluation index.

1. Introduction

The amount and rate of tunnel deformation are not only the important reference indexes of tunnel construction progress and safety, but also dynamic information feedbacks of the ambient environment's influences on the whole tunnel. It is difficult to express tunnel deformation through the quantitative relation formula because it has complicated non-linear relationships with numerous random and indeterminate factors. At present, the deformation prediction methods mainly include the empirical method, theoretical analysis method and intelligent prediction method. The application condition and scope for the calculation formula deduced from the empirical method are limited and there is generally a large deviation between the

[1]School of Transportation Science and Engineering, Harbin Institute Of Technology, Harbin, 150090, China

[2]School of Building Engineering Technology, Heilongjiang Institute of Construction Technology, Harbin, 150050, China

calculating result and the measured value [1]. Numerous factors considered in practical engineering when using the theoretical analysis method largely increase the complexity in formula and thus enhance the difficulty in prediction [2]. Over the recent decades, many intelligent optimization methods have been applied in tunnel deformation prediction such as artificial neural network [3], artificial neural network [4], genetic algorithm [5] and wavelet analysis [6]. Although the above-mentioned methods are applied to some degree and some research achievements have been obtained accordingly, such algorithms need a large number of sample data of observed tunnel deformation amounts and it is rather difficult to acquire such data in reality. As for the weaknesses mentioned above, the Least Square Support Vector Machines (LSSVM) are widely applied to the study of issues with small sample data, because it can solve the tunnel deformation issues characterized by nonlinearity, few samples and high dimension.

In view of the weaknesses such as low precision and the failure of self-adaptive selection of parameters of the prediction method for LSSVM tunnel deformation amount, a tunnel deformation prediction method based on LSSVM optimized by FOA. The predictive study on tunnel deformation amount can be achieved by optimizing the penalty factor C and kernel function parameter g of LSSVM through FOA.

2. Methodology

The Fruit Fly Optimization Algorithm (FOA) is a brand-new swarm intelligence algorithm proposed by Pan Wenchao, who was enlightened by the fruit fly's foraging behavior. With the advantages of few control parameters and rapid convergence rate, the algorithm has been widely applied to the fields of engineering optimization and scientific research. The algorithm flow is shown below [1–2], [7]:

1. Set the *popsize* of fruit flies and the maximum *Iteration* of FOA; randomly initialize the location of fruit fly populations; the initialization results are denoted respectively with X_begin and Y_begin.

2. Calculate the random optimization direction and distance of an individual fruit fly according to next two formulae

$$x_i = X\_begin + Value \times rand(1, N)\,, \tag{1}$$

$$y_i = Y\_begin + Value \times rand(1, N)\,. \tag{2}$$

In formulae (1) and (2), the symbol *Value* denotes the scouting distance of fruit fly; x_i and y_i signify the location of individual fruit fly in next moment.

3. Estimate the distance d_i between an individual fruit fly and the original point. Then, calculate the smell concentration s_i of individual fruit fly. Both variables are given as

$$d_i = \sqrt{x_i^2 + y_i^2}\,, \tag{3}$$

$$s_i = \frac{1}{d_i}\,. \tag{4}$$

4. The smell concentration s_i is substituted into the smell concentration decision function in the next formula to calculate the smell concentration of the current location of the individual fruit fly;

$$Smell_i = Function(s_i)\,. \tag{5}$$

5. Find out the optimum smell concentration value and optimum location in the fruit fly population; the optimum smell concentration is denoted as $Smell_{\mathrm{b}}$; the optimum location is denoted as x_{b} and y_{b}.

6. Keep and record the optimum location and optimum smell concentration of fruit fly; the optimum smell concentration $Smellbest{=}Smell_{\mathrm{b}}$; the initial position of fruit fly $X\_begin{=}x_{\mathrm{b}}$ and $Y\_begin{=}y_{\mathrm{b}}$; meanwhile, the fruit fly population searches for the optimum location.

7. Start the iterative optimization and repeat the iterative steps (2)–(5); meanwhile, judge whether the smell concentration is better than the iterative smell concentration of the previous generation; if so, carry out step (6).

2.1. LSSVM

The LSSVM put forward by Suykens can be converted into [3], [6–7]:

$$J(\omega,\xi) = \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{N}\xi_k^2\,,$$

$$\text{s.t. } y_k = \phi(x_k)\omega^{\mathrm{T}} + b + \xi_k\,, \tag{6}$$

where $\xi_k \geq 0,\ k = 1, 2, \ldots, N$ and C is the penalty factor.

Using the lagrangian method, formula (6) can be converted into

$$L(\omega,b,\xi,\alpha) = \frac{1}{2}||\omega||^2 + C\sum_{i=1}^{N}\xi_k^2 -$$

$$-\sum_{i=1}^{N}\alpha_k[(\omega^{\mathrm{T}}\phi(x_k) + b + \xi_k) - y_k]\,. \tag{7}$$

In formula (7), $\alpha_k,\ k = 1, 2, \ldots, N$ denote the Lagrangian multipliers. Calculate now the partial derivatives of ω, b, ξ and α, and make them equal to zero. Then

$$\omega = \sum_{k=1}^{N}\alpha_k\phi(x_k) = 0\,,$$

$$\sum_{k=1}^{N} \alpha_k = 0\,,$$

$$\alpha_k = C\xi_k\,,$$

$$\omega^{\mathrm{T}}\phi(x_k) + b + \xi_k - y_k = 0\,. \tag{8}$$

According to the Mercer condition, the kernel function $k(x_i, x_j)$ is shown in formula

$$k(x_i, x_j) = \phi(x_i)\phi(x_j)\,. \tag{9}$$

As the RBF kernel function has the ability of nonlinear predictive diagnosis, it is used to achieve the tunnel deformation prediction and the formula is shown below [8, 9].

$$k(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2g^2}\right)\,. \tag{10}$$

Thus, the LSSVM tunnel deformation model is as follows:

$$f(x) = \sum_{i=1}^{m} \alpha_i \exp\left(-\frac{||x_i - x_j||^2}{2g^2}\right) + b\,. \tag{11}$$

In this paper, the penalty parameter C and the kernel function parameter g are used as the objects of optimization and FOA is used to optimize and acquire the optimal LSSVM model.

2.2. FOA-LSSVM tunnel deformation prediction model

Since parameters C and g need to be optimized in LSSVM, the optimized mathematical model is shown below:

$$Fitness = \{C, g\}. \tag{12}$$

After optimization in formula (12), the self-adaptive selection of parameters C and g is achieved in the condition of ensuring minimum error in tunnel deformation prediction. The fitness function can be defined. Suppose the practical amount of tunnel deformation in time t is $y(t)$ and the predicted amount of tunnel deformation is $\hat{y}(t)$, the difference value between the practical amount of tunnel deformation $y(t)$ and the predicted amount of tunnel deformation $\hat{y}(t)$ is formula [10–12]

$$e(t) = \hat{y}(t) - y(t)\,. \tag{13}$$

As for the nonlinear problems in tunnel deformation prediction, suppose the number of data samples of practical tunnel deformation is n, then use the kernel parameter and penalty parameter of LS-SVM optimized by FOA to minimize the quadratic sum of difference value between the practical amount of tunnel deformation and the predicted amount of tunnel deformation of LS-SVM; the fitness function is shown in formula

$$\min Fitness(t) = \frac{1}{2n} \sum_{i=1}^{T} e^2(t) \,. \tag{14}$$

2.3. Algorithm steps

The algorithm steps of FOA-LSSVM-based tunnel deformation prediction are as follows:

Step 1: normalize the tunnel deformation data.

Step 2: set the maximum iteration (*maxgen*) and the population size (*popsize*) of FOA.

Step 3: input the constructed training samples into LSSVM; calculate the fitness function value of individual fruit fly according to the fitness function formula (14); look for individual fruit flies and the locations and optimum values of global optimum individual fruit fly.

Step 4: update the location and search direction of fruit fly.

Step 5: calculate and evaluate the fitness size and update the location and search direction of fruit fly.

Step 6: if $gen > maxgen$, preserve the optimal solution; on the contrary, if $gen = gen + 1$, go to Step 4.

Step 7: achieve the tunnel deformation prediction according to the optimum parameters C and g corresponding to the optimum locations of fruit fly population; the flow chart is shown in Fig. 1:

3. Result analysis and discussion

3.1. Evaluation indexes

To verify the validity of the method, the MSE (mean square error) is used to evaluate the evaluation indexes of the result of tunnel deformation prediction. The MSE formula is shown below [13–17]

$$MSE = \sqrt{\frac{1}{K} \sum_{i=1}^{K} (x_i - \hat{x}_i)^2} \,. \tag{15}$$

In formula (15), x_i and y_i, respectively, signify the practical value of tunnel deformation and the predicated value of tunnel deformation.

3.2. Empirical analysis

To verify the validity of the algorithm in this paper, a tunnel of Guiyang-Guangzhou High-speed Rail was used as the object of study [18–19]. The observation data of tunnel deformation from January 2009 to January 2015 was used as the object of study and predictive study on tunnel deformation was carried out by means of rolling prediction [20]. The FOA parameters are set as follows: the maximum iteration is 100; the popsize is 20. The prediction results are shown in Figs. 2, 3 and 4.

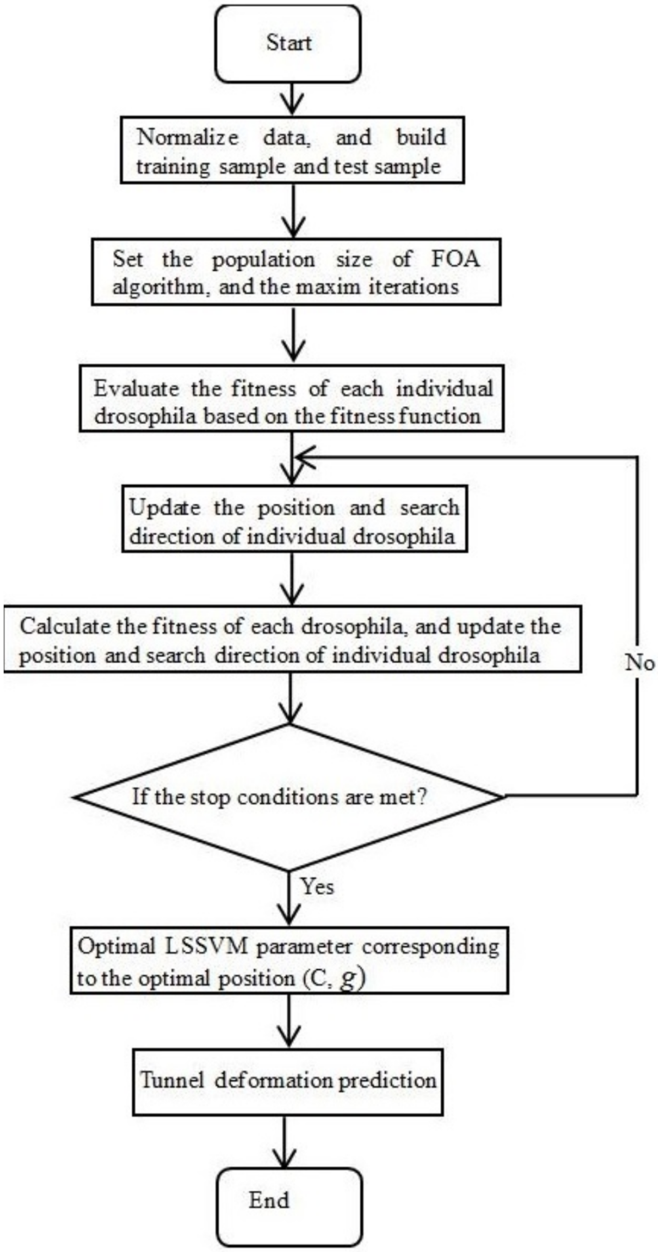

Fig. 1. Flow chart of FOA-LSSVM-based tunnel deformation prediction

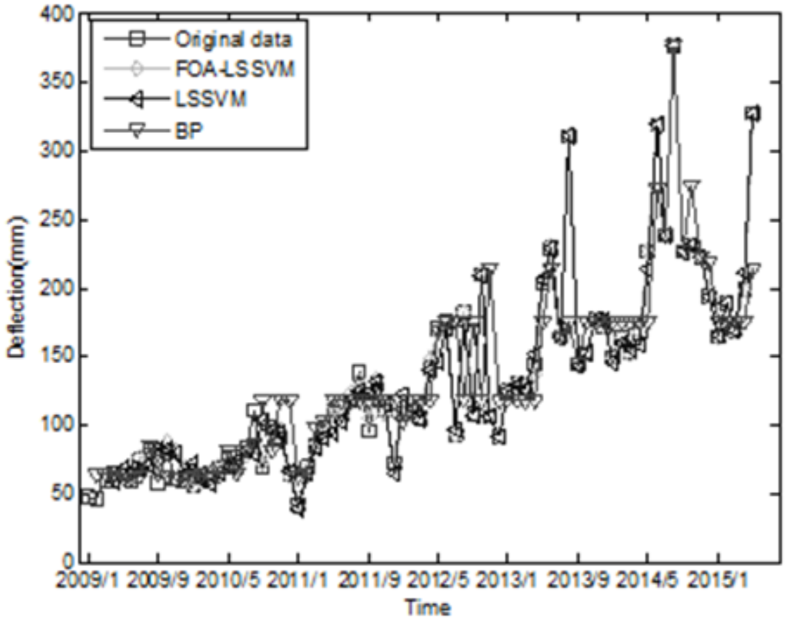

Fig. 2. Diagram of prediction results of FOA-LSSVM, LSSVM and BP algorithms

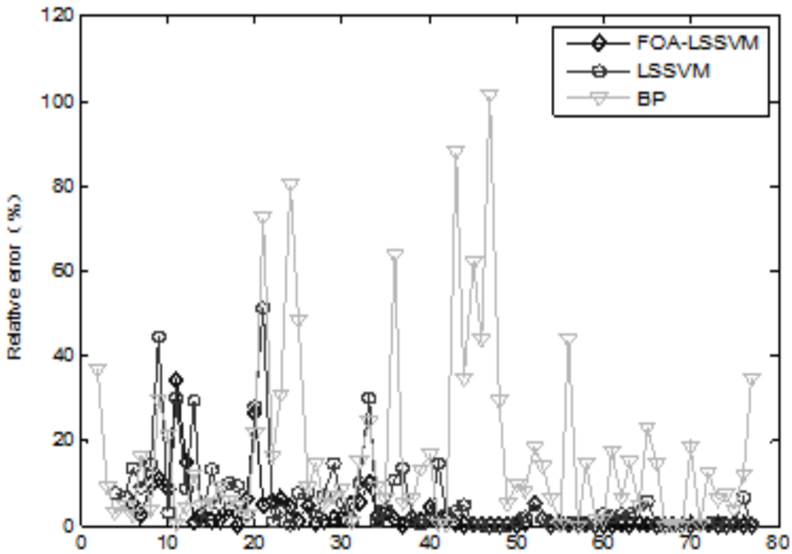

Fig. 3. Diagram of relative errors of prediction of FOA-LSSVM, LSSVM and BP algorithms

It can be seen from the prediction results in Figs. 2 and 3 that the FOA-LSSVM algorithm used in this paper is more precise than the LSSVM and BP algorithms and its mean relative error in prediction is about 4 %. Figure 4 shows the fitness convergence curve of optimized LSSVM through FOA.

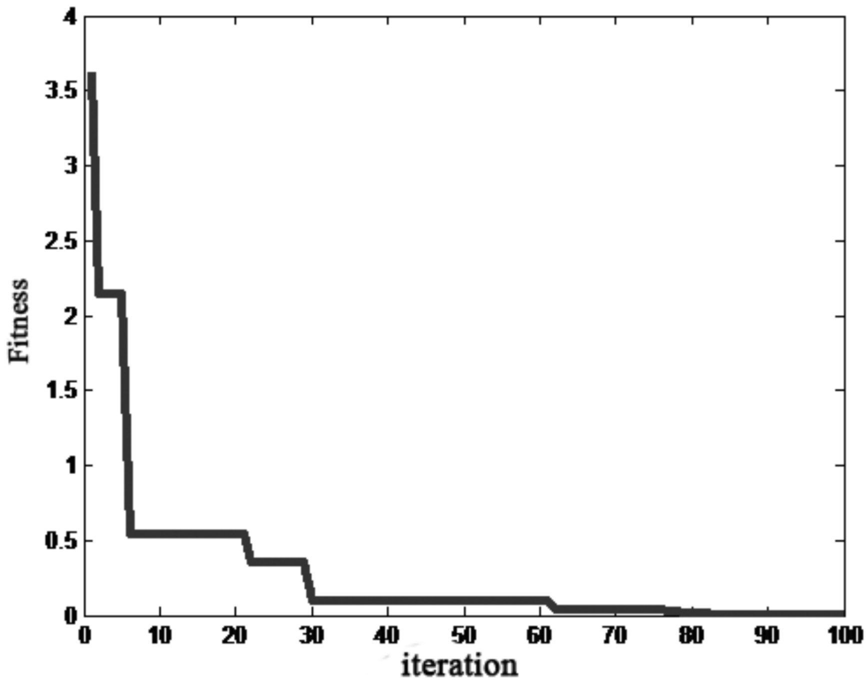

Fig. 4. Curve graph of fitness convergence of optimized LSSVM through FOA

To show the superiority of FOA-LSSVM algorithm, the prediction results of FOA-LSSVM algorithm, LSSVM algorithm [21] and BP [22] algorithm were compared and operated for 10 times; the comparative results are shown in Table 1.

Table 1. MSE comparison in prediction through FOA-LSSVM algorithm, LSSVM and BP algorithm

Times of operation	BP	LSSVM	FOA-LSSVM
1	0.0088	0.0060	0.0040
2	0.0072	0.0055	0.0046
3	0.0068	0.0050	0.0040
4	0.0084	0.0064	0.0042
5	0.0065	0.0056	0.0038
6	0.0074	0.0061	0.0043
7	0.0076	0.0056	0.0035
8	0.0064	0.0046	0.0042
9	0.0072	0.0076	0.0040
10	0.0067	0.0051	0.0047
Mean value	0.0072	0.0058	0.0041

From the comparative results of prediction MSE of FOA-LSSVM algorithm, LSSVM and BP in Table 1, it can be seen that the prediction effect of FOA-LSSVM algorithm is the best and is better than that of LSSVM and BP models; besides, the prediction effect of LSSVM is better than that of BP.

From the comparative results of prediction time of FOA-LSSVM algorithm, LSSVM and BP in Table 2, it can be seen that the prediction time of FOA-LSSVM algorithm is the shortest and is shorter than that of LSSVM and BP model; besides, the prediction time of LSSVM is shorter than that of BP.

Table 2. Comparison of prediction time of FOA-LSSVM, LSSVM and BP algorithms (unit/s)

Predictive step size	BP	LSSVM	FOA-LSSVM
Single step	111.40	97.36	37.21
3	97.60	89.22	34.25
5	86.33	74.22	32.18
7	79.45	65.80	31.27

4. Conclusion

As there are problems such as low precision and failure of self-adaptive selection of parameter in prediction of tunnel deformation by using LSSVM, a prediction method for tunnel deformation based on LSSVM optimized by FOA was proposed. The predictive study on tunnel deformation was achieved by using FOA to optimize the penalty factor C and kernel function parameter g of LSSVM. As shown in the experimental result, the prediction accuracy of FOA-LSSVM is higher than that of LSSVM and BP and the prediction time and MSEP of FOA-LSSVM are also more superior, so the validity and reliability of using FOA-LSSVM to predict tunnel deformation are verified. Therefore, this method can be popularized in other fields to solve other similar issues.

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