Application of dam deformation prediction based on LSSVR optimized by ASA-ABC

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Abstract. In order to improve the prediction accuracy of the dam deformation, aiming at the difficulty to determining the parameters of the least squares support vector regression (LSSVR) and the artificial bee colony algorithm (ABC) is prone to fall into local optimum when optimizing parameters, a self-adaptive simulated annealing mechanism is designed to improve the optimization performance of the ABC algorithm, so that a prediction model based on least squares support vector regression optimized by adaptive simulated annealing artificial bee colony (ASA-ABC-LSSVR) is constructed, and the model is applied to dam deformation prediction. The experimental results show that ASA-ABC effectively solves the difficult to balance the development and exploration capability of ABC. Compared with the prediction model based on the LSSVR and the model based on the LSSVR optimized by ABC (ABC-LSSVR), the ASA-ABC-LSSVR model has higher prediction accuracy and the prediction trend is more practical.

1. Introduction
Dam deformation is a complex nonlinear dynamic system [1], and its deformation is affected by various factors such as load, hydrology, and geology and construction quality. At present, most commonly used deformation prediction methods include regression analysis, time series analysis, and grey model and so on [2]. However, these methods have some limitations [3]. For example, the prediction accuracy of regression analysis model is largely dependent on whether the selection of modeling factors is appropriate; time series analysis mainly focuses on long time series monitoring data; the grey prediction model has higher requirement of the original data, and the prediction accuracy is reduced when the original data series fluctuates greatly. Support vector regression (SVR) is a new statistical method [4], which is proposed by the Vapid in 1990s to deal with many problems, such as regression and pattern recognition. Least squares support vector regression (LSSVR) is an extension of SVR, it can transform the quadratic programming problem of SVR into solving linear equations, and simplify

The calculation. LSSVR also inherits a series of advantages of SVR, such as its unique advantages in dealing with small sample and high-dimensional problem and its powerful generalization function. However, as with SVR, it is difficult for LSSVR to value the parameters. In recent years, many intelligent algorithms with heuristic feature have been applied in the optimization field, and which have played an important role in scientific research and practical engineering. Artificial bee colony algorithm (ABC) is a biological intelligent optimization algorithm proposed by Parabola [5] in 2005,
which simulates bee colony to search for nectar source. Literature [6] shows that the comprehensive performance of ABC is one of the best algorithms by analyzing and comparing the performance of several popular intelligent optimization algorithms such as PSO, GA, ABC and so on. But due to the limitations of the choice strategy ABC is easy to fall into local optimal solution.

In view of the defects of the ABC, this paper combines the improved simulated annealing algorithm (SA) with the ABC, and proposes an adaptive simulated annealing artificial bee colony (ASA-ABC). A new adaptive cooling function is designed for the SA, and the annealing mechanism of the SA is applied to the nectar source selection of the ABC, so that the exploration and development ability of the ABC can be balanced. Considering the prediction accuracy of LSSVR as the target function, and optimizing the penalty parameters and kernel parameters of LSSVR by ASA-ABC, then the deformation prediction model based on LSSVR optimized by ASA-ABC is established, and the model is applied to a dam.

2. Basic theories

2.1. Simulated annealing

Simulated annealing algorithm was put forward by Metropolis [7] in 1953, and it was applied to solve the combination optimization problem after 30 years by Kirkpatrick [8]. The basic theory of simulated annealing algorithm is similar to the physical annealing process of solid. The specific process is as follows [9, 10]:

(1) Initialization: initial temperature $T_0$, initial solution $W$ and cooling function $T(t)$;

$$
T(t) = T(t-1) \cdot \sigma
$$

In the formula, $\sigma$ is the cooling coefficient, $t$ is the number of iterations.

(2) Searching a new solution $V$, and calculating the target function value $f(W)$ and $f(V)$;

(3) Calculating the difference of target function;

$$
\Delta f = f(V) - f(W)
$$

(4) When $\Delta f \leq 0$, a new solution $V$ is accepted; otherwise, when $\Delta f > 0$, a new solution $V$ is accepted by probability $P$.

$$
P = e^{\frac{-(f(V) - f(W))}{kT}}
$$

In the formula, $k$ is the Boltzmann constant?

(5) With the decrease of temperature, steps (2) – (5) are iterated until the termination condition of algorithm is satisfied.

2.2. Artificial bee colony

ABC is an intelligent algorithm according to the whole process of honeybee collecting honey. The whole population can be divided into leader, follower and scouter, and the leaders and followers account for half of the size of the whole population. The process of finding the food source by bees can be abstracted into the process of searching for the optimal solution of the problem [11], three kinds of bees do their jobs and work efficiently in a collaborative way. The optimization theory [12] is as follows:
Food source $x_i (i=1,2,...,NP)$, the quality of $x_i$ corresponds to the fitness value of the solution. The dimension of the solution is $D$, the number of iterations is $t$, the maximum iteration number is $\text{maxCycle}$, so the food source position is $x_i^{'} = [x_{i1}^{'}, x_{i2}^{'}, ..., x_{iD}^{'}]$ when the number of iterations is $t$, $x_{id} \in (L_d, U_d)$ is the upper and lower bounds of the search space.

(1) The initial position of random generation of Solutions:

$$x_{id} = L_d + \text{rand}(0,1) \cdot (U_d-L_d)$$

(4)

(2) A new solution is generated around the initial solution:

$$v_{id} = x_{id} + \phi (x_{id} - x_{jd})$$

(5)

$j = 1,2,...,NP$ And $j \neq i$, $\phi$ is a random number satisfies the uniform distribution in $[-1, 1]$.

(3) Evaluating the fitness of the two source, according to the greedy algorithm to retain $x_i$ or $v_i$:

$$\text{fit} = \begin{cases} 
1/\left(1 + f_i\right), & f_i \geq 0 \\
1 + \text{abs} \left(f_i\right), & \text{Others}
\end{cases}$$

(6)

$f_i$ is target function value.

(4) Calculating the followed probability of food source by leaders:

$$P_i = \text{fit}_i \sum_{i=1}^{NP} \text{fit}_i$$

(7)

(5) Followers choose the leaders by roulette, that is to say, a random number with uniform distribution is produced in $[0, 1]$ which called $r$, when $P_i > r$, followers produces a new solution $i$, determine the retention of solution by the greedy algorithm.

(6) Whether the solution is met to abandon? Whether there has a better solution before the iterations reach the threshold?

Give up: leader into the scouter, then generating a new solution randomly in the search space instead of $x_i$:

$$x_i^{t+1} = \begin{cases} 
L_d + \text{rand}(0,1) \cdot (U_d-L_d), & t \geq \text{limit} \\
x_i^{'}, & t < \text{limit}
\end{cases}$$

(8)

Not give up: $t = t+1$, output the optimal solution until the algorithm reaches the termination condition.
2.3. Least squares support vector regression

The basic idea of LSSVR is to draw a best fitting function by using the known sample data, and then input the new sample data according to this function, so as to calculate the corresponding output value. The specific step [13] is:

1. Giving a training set:

\[ T = \{(x_1, y_1), \ldots, (x_l, y_l)\} \in (R^n \times Y)^l \]  

\[ x_i \in R^n, y_i \in Y, i = 1, \ldots, l \]

2. Mapping sample input to high-dimensional space by nonlinear mapping, and constructing LSSVR's function:

\[ y(x) = \omega^T \phi(x) + b \]  

\( \omega \) is a weight vector, and \( b \) is a deviation.

3. Turn it into the following optimization problem:

\[ \min_{\omega, b, \xi} R = \frac{1}{2} \| \omega \|^2 + \frac{c}{2} \sum_{i=1}^{l} \xi_i^2 \]  

s.t. \[ y_i = \omega^T \phi(x_i) + b + \xi_i \]  

\( c \) is the penalty parameter, and \( \xi_i \geq 0 \) is the relaxation factor.

4. The function model of LSSVR can be solved by using Lagrange function and KKT optimization condition:

\[ y(x) = \sum_{i=1}^{l} a_i K(x, x_i) + b \]  

where \( a_i \) is the lagrange multiplier and the \( K(x, x_i) \) is a kernel function.

3. Adaptive simulated annealing artificial bee colony

ABC has better ability to obtain extreme value, but it is hard to balance its development ability and exploration ability. But each iteration of SA reflects the balance between the two strategies of centralization and diffusion. Therefore, combining SA with ABC constitutes SA-ABC, taking the ABC as the main body, and the annealing mechanism in SA is used to replace the greedy mechanism in ABC. When the target function value of the new solution is larger than the target function value of the current solution, the new solution is still accepted in a certain probability, which enriches the diversity of the population and reduces the probability of obtaining a local optimal solution.

In the SA algorithm, the decreasing way of temperature is reflected by the cooling function, and the temperature determines whether the algorithm is centralized or diffused. If the cooling is too slow, the number of cycles is increased and the convergence efficiency of the algorithm is low; if the cooling is too fast, the algorithm quickly turns from wide area search into local search, and it is easy to fall into
local optimal solution. So in the early stage of iteration, this paper hope that the cooling rate is faster to improve the convergence speed; in the later period of iteration, the cooling rate slows down so that it can carry out fine search. Considering formula (1), $T(t)$ is controlled by the cooling coefficient, but the cooling coefficient is constant, so it can't meet the speed variation requirement of temperature. Therefore, this paper designs an adaptive cooling function as follows:

$$T(t) = \frac{T(0)}{\log_2(t+1)}$$

In the formula, $T_0$ is the initial temperature, and $t$ is the number of iterations. From the improved cooling function (14), it can be seen that the temperature decreases from the beginning at a faster rate, and with the increase of the number of iterations, the temperature decreases at a slower rate at the later stage, so the adaptive cooling function has a better optimization efficiency compared to the original cooling function.

Adding the ASA to ABC so that the ASA-ABC is formed, the specific process is as follows:

1. Initialization parameter: the number of bees is $NP$, maximum number of search times is limit, and maximum iteration number of algorithm is maxcycle, $T_0$, $k$

2. The leader search for a new food source $V$ around the initial food source. Calculating the profitability of the current food source and the profitability of the new food source respectively and their difference, choosing a current food source according to ASA:

$$\Delta f = f(V) - f(W)$$

When $\Delta f \leq 0$, accept the new food source;
When $\Delta f > 0$ and $P > rand()$, accept the new food source, otherwise, refuse the new food source.

$$P = e^{[-(f(V)-f(W))]}/kT$$

$$T(t) = \frac{T(0)}{\log_2(t+1)}$$

(3) Followers choose the leaders by roulette, and explore in the neighbourhood of the current source. Choosing a current food source according to ASA:

4. Whether the solution is met to abandon? Whether there has a better solution before the iterations reach the threshold?

(5) give up: leader into the scouter, and continue to search; not give up: repeat the above steps until the termination condition is met.

4. Prediction model based on ASA-ABC-LSSVR

Taking the deformation prediction accuracy of LSSVR as the target function value of the ISA-ABC algorithm, and the ISA-ABC algorithm is used to optimize the penalty parameter and the kernel function parameter of LSSVR, thus the deformation prediction model is constructed. The detailed steps are as follows:
(1) Data preprocessing: normalized computation (mapminmax);

\[ y = \frac{(y_{\max} - y_{\min})(x-x_{\min})}{x_{\max} - x_{\min}} + y_{\min} \]  

(17)

(2) Initialization parameter: the number of bees is NP, maximum number of search times is limit, and maximum iteration number of algorithm is maxCycle, T_0, k

(3) Target function setting: in order to get the prediction value with minimum error, this paper take the minimum root mean square error of LSSVR as the target function of ASA-ABC;

\[ \min f(c, \sigma) = \sqrt{\frac{1}{l} \sum_{i=1}^{l} [y_i - g(x_i, c, \sigma)]^2} \]  

(18)

Among them, l is the sample data set, yi is the measured value, and g is the calculated value of the model.

(4) Optimizing two parameters of LSSVR to obtain optimal parameter solution by ISA-ABC;

(6) Output all the predicted values and calculate the prediction error.

5. Engineering example

Taking the southwest horizontal displacement data of a concrete dam of literature [14] as an example, the dam is set up 7 horizontal displacement monitoring points during the monitoring time, there is 21 periods data of D4 are selected to validate the algorithm. The monitoring data are shown in Table 1. The first 16 period’s data are applied to model fitting, and the last 5 period’s data used to forecast. In order to verify the prediction effect of the model, LSSVR [14] model and ABC-LSSVR model were used for prediction and comparison.

| Periods | Monitoring data /mm | Periods | Monitoring data /mm | Periods | Monitoring data /mm |
|---------|---------------------|---------|---------------------|---------|---------------------|
| 1       | 6.2                 | 8       | 8.5                 | 15      | 8.2                 |
| 2       | 5.8                 | 9       | 8.2                 | 16      | 11.7                |
| 3       | 6.1                 | 10      | 8.0                 | 17      | 13.4                |
| 4       | 6.0                 | 11      | 7.8                 | 18      | 12.6                |
| 5       | 6.4                 | 12      | 7.5                 | 19      | 15.6                |
| 6       | 8.5                 | 13      | 7.2                 | 20      | 14.2                |
| 7       | 11.1                | 14      | 7.0                 | 21      | 16.3                |

The parameter setting of the ASA-ABC-LSSVR model: the dimension of problem is 2, the maximum numbers of iteration is 100, the maximum number of search times is 50, the range of the penalty parameter value and the kernel function parameter value is (0.01, 100), the initial temperature is 100, and the Boltzmann constant is 1. Writing the ABC-LSSVR model and ASA-ABC-LSSVR model program by mat lab, then the population evolution diagram of each model is shown in Figure 1, and the prediction results of each model are shown in Table 2 and Figure 2.
Table 2. The prediction results of each model

| Periods | Monitoring data /mm | LSSVR [18] | ABC-LSSVR | ASA-ABC-LSSVR |
|---------|---------------------|------------|-----------|---------------|
|         | Predictions /mm     | Relative error (%) | Predictions /mm | Relative error (%) | Predictions /mm | Relative error (%) |
| 17      | 13.4                | 12.800     | 4.47      | 13.690        | 2.16           | 13.400          | 0               |
| 18      | 12.6                | 12.767     | 0.60      | 12.309        | 2.31           | 12.388          | 1.68            |
| 19      | 15.6                | 15.231     | 2.36      | 15.394        | 1.32           | 15.376          | 1.44            |
| 20      | 14.2                | 14.396     | 1.38      | 14.203        | 0.02           | 14.068          | 0.93            |
| 21      | 16.3                | 16.172     | 0.78      | 16.101        | 1.22           | 16.299          | 0.01            |
| Average |                     | 1.918      | 1.406     | 0.812         |                |                |                 |

Figure 1. Predictive evolutionary graph of ABC-LSSVR and ASA-ABC-LSSVR

Figure 2. The prediction results of each mode

Population evolution analysis: according to Figure 1, in the early stage of iteration, the iterative curve of the ASA-ABC-LSSVR model did not decline as quickly as ABC-LSSVR, but experienced a period of stationary phase, which indicating the simulated annealing mechanism interference the selection of solutions, so that ASA-ABC-LSSVR model accept some differential solutions and enrich the diversity of the population. In the middle iteration stage, with the rapid decline of temperature, the
probability of accepting bad solution of ASA-ABC-LSSVR model decreases, and the iteration curve decreases rapidly. In the later stage of iteration, because of a slower pace of declines of the temperature, ASA-ABC-LSSVR model can search for the solution more accurately, and find the optimal solution. Compared with the entire iterative curve of the ABC-LSSVR model and the ASA-ABC-LSSVR model, the ASA-ABC-LSSVR model has a better balance during the development and exploration ability of the ABC algorithm, and it finds a more accurate parameter solution than the ABC-LSSVR.

Prediction results analysis: according to Table 2, the average relative errors of LSSVR model, ABC-LSSVR model and ASA-ABC-LSSVR model are 1.918%, 1.406% and 0.812% respectively, so that the prediction accuracy of ASA-ABC-LSSVR model is the highest. As also shown in Figure 2, the deformation predicted curve by the ASA-ABC-LSSVR model is most consistent with the actual monitoring deformation curve, which can better reflect the trend of deformation.

6. Conclusion
In the deformation monitoring of dam, it has great significance for the safety operation of dam to predict accurately. This paper is aimed at the shortcomings of the ABC algorithm. An adaptive simulated annealing mechanism is designed to balance the development and exploration capability of ABC algorithm, and the dam deformation prediction model is constructed by combination with LSSVR. According to the experimental results, it is easy to know ASA-ABC algorithm finds a better parameter solutions for LSSVR than ABC algorithm. Meanwhile, ASA-ABC-LSSVR model has higher prediction accuracy than LSSVR model and ABC-LSSVR model, and it is more consistent with the trend, which has a certain practical value.

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