Application of Improved Sparrow Search Algorithm in Concrete

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Abstract—Compared with other algorithms, the performance of sparrow algorithm is better, but it also has shortcomings such as insufficient convergence and large randomness. For this reason, this paper proposes an improved sparrow search algorithm, which uses K-means to initialize the population to reduce the influence of randomness. Use sine and cosine search to improve the quality of the position of followers, and finally use adaptive local search to update the optimal solution, and apply it to concrete strength prediction. The results show that various improved sparrow search algorithms have certain advantages and high stability.

1. Introduction
SVR (Support Vector Regression) is a "tolerant regression model", which is an application of SVM to regression problems. Its generalization performance is relatively good, and it is not prone to overfitting, and it can achieve good performance with very little data. It has a good effect on regression prediction. Its advantages are mainly reflected in its ability to deal with small samples, regression and some high-dimensional recognition problems with high precision[1]. Currently, it has been applied by public researchers in many fields, such as medical image, fault diagnosis, intrusion detection and so on[2].

SVR is an application of SVM, and the basic idea is the same. It can be seen from the characteristics of SVR's mathematical model that it is very important to select appropriate parameters, because it directly determines the pros and cons of the model's performance. The traditional SVR parameter selection is to directly give an interval, and then randomly select from the interval. However, the random selection of parameters also brings some defects, such as over learning or under learning. In addition, due to the instability of randomly selected parameters, there will be great differences in the accuracy of the test set. For the problem of parameter selection, intelligent optimization algorithm opens up a new way, which can quickly find the best parameters and achieve the best prediction effect. Nowadays, most of the algorithms used for SVR parameter selection are intelligent optimization algorithms. As two classical algorithms, GA and PSO have achieved good results in the selection of SVR parameters. However, these two algorithms are not perfect and have some defects. Precocity is the biggest problem of GA algorithm. It has insufficient global search ability and is easy to converge to the local optimal solution[3-5]. It is not sensitive to the objective function and has poor stability, so it is not practical in optimizing SVR model. The PSO algorithm has many problems in the search space, such as loss of population diversity, easy to fall into a local minimum, easy to premature convergence, and poor local optimization ability.

According to the shortcomings of the current algorithm, the paper puts forward an improved
SSA (Sparrow Search Algorithm) for SVR parameter selection. In 2020, SSA was put forward. It’s a new swarm intelligence optimization algorithm. It has simple structure and clear principle. Its function optimization ability has exceeded that of PSO and GA, but it hinges on the initialization stage \[6\]. In addition, it has a high probability of falling into local optimization during the optimization process. In this paper, aiming at the defects of SSA algorithm, two improved SSA algorithms based on adaptive local search and K-means sine cosine search are proposed. To judge by comparing the result of the experiment which improvement strategy has high adaptability and strong optimization ability.

2. Sparrow search algorithm

In the process of foraging for food, sparrows are divided into two categories: explorers and followers. The explorer leads the entire group in foraging behavior, because this type of sparrow has a wide range of exploration. Their duty is to provide foraging places and future directions for the race, and the followers are to use the information provided by the explorers to eat to fill their stomachs. All individuals in the population will monitor each other's behavior\[8\]. In addition, the natural enemies of the population will compete with the companions who eat a lot of food resources to increase their predation rate\[9\].

The explorer’s location update formula is as follows:

\[
T_{i,j}^{t+1} = \begin{cases} 
T_{i,j}^t \cdot \exp\left(\frac{-b}{a \cdot Z}\right) & \text{if } R_2 < ST \\
T_{i,j}^t + Q \cdot L & \text{if } R_2 \geq ST
\end{cases}
\]  \hspace{1cm} (1)

In formula (1), \(b\) is a constant, indicating the number of iterations, and \(Z\) is a fixed value, indicating the maximum number of iterations. \(T_{i,j}\) represents the current position information of the i-th sparrow in the j-th dimension\[10\]. \(a \in (0,1]\) is a random number. \(R_2 (R_2 \in [0,1])\) represents a warning value, \(ST (ST \in [0.5,1])\) represents a safe value. \(Q\) is a random number that obeys a normal distribution. \(L\) represents a \(1 \times n\) matrix, in which all elements are 1. When \(R_2 < ST\), it means that no attacker (natural enemy) is found around the group environment at this time, and it is in a safe state. The explorer can lead the group to forage.\[11\]. When \(R_2 \geq ST\), it means that the individual in the group has found the attacker and issued an alarm, the whole group will stop eating, and the explorer will immediately lead the group to take emergency escape.

The location update description of the follower is as follows:

\[
T_{i,j}^{t+1} = \begin{cases} 
Q \cdot \exp\left(\frac{T_{\text{worst}}^t - T_{i,j}^t}{t^2}\right) & \text{if } i > n/2 \\
T_{p}^{t+1} + \left|T_{i,j}^t - T_{p}^{t+1}\right| \cdot A^+ \cdot L & \text{otherwise}
\end{cases}
\]  \hspace{1cm} (2)

In formula (2), \(T_p\) represents the best position to escape from natural enemies, while \(T_{\text{worst}}\) represents the worst position. \(A\) is a \(1 \times d\) matrix whose elements are only 1 or -1, where \(A^+ = A^T (AA^T)^{-1}\). When \(i > n/2\), Sparrow populations will make emergency avoidance behaviors when it is aware of danger. The location update description is as follows:

\[
T_{i,j}^{t+1} = \begin{cases} 
T_{\text{best}}^t + \beta \cdot \left|T_{i,j}^t - T_{\text{best}}^t\right| & \text{if } f_i \neq f_g \\
T_{i,j}^t + K \cdot \left(\frac{T_{i,j}^t - T_{\text{worst}}^t}{f_i - f_w} + \varepsilon\right) & \text{if } f_i = f_g
\end{cases}
\]  \hspace{1cm} (3)

In formula (3), \(T_{\text{best}}\) is currently the fastest location to escape danger. \(\beta\) is the control step parameter, which is a random number that obeys the standard normal distribution. \(K \in [-1,1]\) is a random number, and \(f_i\) represents the degree of adaptation of the individual sparrow to the current environment. \(f_g\) represents the best fitness value in the current search range; on the contrary, \(f_w\) represents the worst fitness value in the current search range. \(\varepsilon\) is a real number that is infinitely close to 0, and its function is to prevent the denominator from being 0. When \(f_i \neq f_g\), it means that this sparrow is at the boundary of the foraging range and is easily attacked by natural enemies. It needs to move closer to the center of the population\[12-14\]. When the values of \(f_i\) and \(f_g\) are equal, it indicates that some sparrow individuals are aware of the approaching danger and need to take hedging behavior. \(K\) represents the moving step length.
of the sparrow.

3. Improved sparrow search algorithm

3.1. Sine cosine search strategy

In the SSA optimization process, the location of the follower follows the discoverer and changes accordingly, which leads to the loss of independence of the follower and dependence on the discoverer. Therefore, the food obtained is not necessarily the best quality, and it is easy to lead to the low fitness value of some followers. The sine and cosine search strategies are introduced. After each update of the follower's position, sine and cosine search is carried out to update the best position nearby. In this way, the reliability of the position of each iteration is improved, and it is easy to obtain the global optimal solution. The definition of sine and cosine search is given below:

\[
Y(t+1) = \begin{cases} 
Y(t) + r_3 \times \sin(r_4) \times D_r \leq 0.5 \\
Y(t) + r_3 \times \cos(r_4) \times D_r \geq 0.5
\end{cases}
\]

\[
D = \{|r_6 \times Y_i(t) - Y_j(t)| i = 1,2, ..., d\}
\]

\[
r_3 = a - a \times \frac{t}{M}
\]

In the above formula, the value of \(r_3\) will increase linearly with \(m\) (the number of iterations), \(a=2\), \(r_4 \in (0,360^\circ)\), \(r_5\) and \(r_6\) are random numbers between \([0,1]\), and follow a uniform distribution. It can be seen from the above that its function is to improve the convergence accuracy of the algorithm to a certain extent and effectively prevent premature maturity.

3.2. K-means

K-means believes that the closer the distance between two targets, the greater the similarity. The most commonly used classic clustering algorithm based on Euclidean distance. The algorithm has low complexity, easy to understand, and good clustering effect. The advantage of this algorithm is that when dealing with large data sets, it can guarantee better scalability and is easy to implement. It is currently widely used in data preprocessing, signal classification.

The initialization of swarm intelligence optimization algorithm has randomness, which leads to differences in the final results, and it is also possible to fall into local optimization\[15\]. K-means is used to initialize the population, which makes the individual distribution fully uniform, reduces the impact of randomness, and brings great convenience for subsequent optimization.

3.3. Adaptive local search

The optimal solution found by sparrow individual after one iteration is not necessarily reliable. If it encounters local extreme points, it will limit the optimization ability of subsequent algorithms. Therefore, it is necessary to introduce adaptive local search to search the neighborhood of the current optimal location again, compare the solution found this time with the previous one, and update the optimal solution. The formula of adaptive local search is as follows:

\[
Y(t+1) = (1 - \varepsilon)Y(t) + \varepsilon Rand
\]

\[
\varepsilon = \frac{W - t + 1}{W}
\]

Among them, \(Rand\) is a d-dimensional vector, \(Rand(i)\) is a random number on \([0,1]\) and obeys a uniform distribution, and \(W\) is the number of iterations.

3.4. Improved sparrow search algorithm flow

The improved algorithm proposed in this paper is divided into two types, they are all based on the K-means clustering algorithm, one is based on this, adding a sine-cosine search strategy called SSSA, and the other is adding an adaptive search strategy SSA Called\[16-17\]. Take ASSA as an example, briefly
introduce the improved algorithm process proposed in this article:

1. Set the number of iterations and populations, and initialize the population location.
2. The value of K is determined according to the initial state of the population, and then the heavy fist is gathered into several different classes. Generally, K cannot be too large, which will make individuals close to the boundary, which is not conducive to finding the best food solution.
3. Calculate the fitness function of every cluster, get the optimal location and worst location.
4. Set up early warning values to update the location of the explorer according to the early warning values.
5. Update the location of followers according to the above formula.
6. Calculate the position of the sparrow that is aware of the danger according to the above formula.
7. Whether the number of iterations has reached the requirement; if so, go to the next step. If not, return to step (3).
8. Get the optimal solution.

The SSSA algorithm is similar to the above process, add the following after step (5): Perform a sine cosine search on the follower's current location neighborhood to find a more reliable position and delete step (6).

4. SVR overview

SVR is an application model of support vector machines on regression problems. The SVR model is dependent on training data. Because the loss function of the built model ignores any training data close to the model prediction (within the interval threshold \( \varepsilon \)), it is lost Important implied information. When SVR is used for non-linear separable data, there are many regression problems that are not linearly regresible in the input space. At this time, the main tool of kernel function is needed\(^{[16-17]}\). The function of kernel function is to map data sample points to higher dimensions. realize the inseparable conversion of the low-dimensional space to the linearly separable mode of the high-dimensional space, and obtain more useful information.

Let the training set sample group comprising one training sample is \( \{(x_i, y_i), i=1, 2, 3, ..., l\} \), in which \( x_i(x_i \in \mathbb{R}^d) \) is the input column vector of the ith training sample, \( x_i = [x_i^1, x_i^2, ..., x_i^d]^T \), \( y_i \in \mathbb{R} \) is \( x_i \) computed to the corresponding output value\(^{[18]}\). The linear regression function established in the high-dimensional feature space is:

\[
\hat{f}(x) = w \cdot \phi(x) + b
\]  

(9)

In equation (10), \( \phi(x) \) is a nonlinear mapping function. Definition \( \varepsilon \) is a linear insensitive loss function:

\[
L(f(x), y, \varepsilon) = \begin{cases} 
0, & |y - f(x)| \leq \varepsilon \\
|y - f(x)| - \varepsilon, & |y - f(x)| > \varepsilon
\end{cases}
\]

(10)

In equation (11), \( f(x) \) is the calculated value of the linear regression function, and \( y \) is the corresponding value of \( x \) in the data set\(^{[19]}\).

Similar to SVM classification, relaxation variables are introduced \( \xi_i, \xi_i^* \), contact the above questions:

\[
\min \frac{1}{2} \|w\|^2 + W \sum_{i=1}^{l} (\theta_i + \theta_i^*)
\]

\[
\text{s.t. } \begin{cases} 
\theta_i - \xi_i - b \leq \varepsilon + \theta_i^* \\
\theta_i^* > 0, \theta_i^* \geq 0
\end{cases}
\]

(11)

In equation (12), \( W \) is the penalty factor, and its value is proportional to the punishment intensity of the sample (training error greater than \( \varepsilon \)). \( \varepsilon \) specifies the criterion for becoming a regression function, and its value is proportional to the error of the regression function.
To solve the above problems, the Lagrange function is also introduced and transformed into dual form:

\[
\begin{aligned}
\max_{\alpha, \alpha^*} & \left[ -\frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} (\alpha_i - \alpha_i^*) (\alpha_j - \alpha_j^*) K(x_i, x_j) \\
& - \sum_{i=1}^{l} (\alpha_i + \alpha_i^*) \epsilon + \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) y_i \right] \\
\text{s.t.} & \left\{ \begin{array}{l}
\sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0 \\
0 \leq \alpha_i \leq C \\
0 \leq \alpha_i^* \leq C
\end{array} \right.
\end{aligned}
\]

(12)

In equation (13), \( K(x_i, x_j) = \varphi(x_i) \varphi(x_j) \) is a kernel function. To suppose the optimal solution of the solving formula is \( \alpha = [\alpha_1, \alpha_2, \ldots, \alpha_l], \alpha^* = [\alpha_1^*, \alpha_2^*, \ldots, \alpha_l^*] \), therefore,

\[
w^* = \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \varphi(x_i)
\]

(13)

\[
b^* = \frac{1}{N_{\text{nsv}}} \left\{ \sum_{0 < \alpha < \alpha_i} [y_i - \sum_{x_i \notin \text{SV}} (\alpha_i - \alpha_i^*) K(x_i, x_j) - \epsilon] + \sum_{0 < \alpha < \alpha_i} [y_i - \sum_{x_i \notin \text{SV}} (\alpha_i - \alpha_i^*) K(x_i, x_j) + \epsilon] \right\}
\]

(14)

In equation (15), \( N_{\text{nsv}} \) is the number of support vectors. Therefore, the regression function is:

\[
f(x) = w^* \varphi(x) + b^*
\]

\[
= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) \varphi(x_i) \varphi(x) + b^*
\]

\[
= \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) K(x_i, x) + b^*
\]

(15)

In equation (16), there are only some parameters \( (\alpha_i - \alpha_i^*) \) is not 0, and its corresponding sample, \( x_i \) is the support vector machine in the problem.

To sum up, the final function form of SVR is basically the same as that of SVM. The selection of \( C \) and \( G \) is a crucial problem for SVM classifier using RBF kernel function. The value of \( C \) determines the importance of the sample to outliers. The larger the value of \( C \), the more attention to outliers, but the more constraints to be met, so it is easy to over fit and the classification model is more complex. On the contrary, the smaller \( C \) is, the less fitting will appear. \( G \) is related to the width and range of the input sample. The larger \( G \) is, the smaller the complexity of projection space is, and the smaller the linear separability of data is; On the contrary, the larger the complexity of projection space, it is easy to lead to serious over fitting phenomenon. It can be seen that reasonable parameters are needed to improve the classification accuracy of SVM model.

5. Prediction of compressive strength of SVR concrete based on improved SSA

In this experiment, 103 groups of actual project detection and test data were collected using standard case datasets, 80 groups of data were taken as training sets, and the remaining 23 groups of data were used as test sets to verify the prediction results.

Forecast process:

1. The obtained data is divided into two parts, one part as the SVR learning sample and the other part as the test sample, and the SVR parameters are optimized by each algorithm.
2. Preprocess and normalize the selected data.
3. Using the prediction accuracy as the objective function, the two improved algorithms are used to
optimize the parameters. This get the optimal parameters of C and G.

(4) The optimal parameters of SVR are obtained.

(5) The optimal network model of Support Vector Machine is used to model training samples, and the prediction model of concrete compressive strength is established.

(6) Testing the test samples with the established prediction model of concrete compressive strength.

(7) Output the predicted compressive strength of concrete.

6. Simulation result

In this experiment, error (MSE) and generalization coefficient (R2) are used to measure the effect of diaphragm type. The specific formula is as follows:

\[ E = \frac{1}{l} \sum_{i=1}^{l} (y_i^* - y_i)^2 \]  
\[ R^2 = \frac{(l \sum_{i=1}^{l} y_i^2 - \sum_{i=1}^{l} y_i^* \sum_{i=1}^{l} y_i)^2}{(l \sum_{i=1}^{l} y_i^2 - (\sum_{i=1}^{l} y_i^*)^2)(l \sum_{i=1}^{l} y_i^2 - (\sum_{i=1}^{l} y_i)^2)} \]

In the two formulas, \( l \) is the number of samples in the test set, \( y_i \) is the real value of the \( i \)-th sample, \( y_i^* \) is the predicted value of the \( i \)-th sample, and \( i = (1,2,\cdots,l) \).

To make the experiment more convincing, PSO and GA algorithms are also compared in this experiment. The prediction accuracy of the training set and the test set is shown in the Figure.1. The running time is shown in Table.1.

(a) SSSA-SVR training set prediction chart  
(b) SSSA-SVR training set prediction chart  
(c) ASSA-SVR training set prediction chart  
(d) ASSA-SVR training set prediction chart
Fig. 1 prediction diagram of various algorithms

(e) SSA-SVR training set prediction chart

(f) SSA-SVR training set prediction chart

(g) PSO-SVR training set prediction chart

(h) PSO-SVR training set prediction chart

(i) GA-SVR training set prediction chart

(j) GA-SVR training set prediction chart
Table.1 optimization prediction results

| Optimization Model | Training Set MSE | R² | Test Set MSE | R² | Running Time |
|--------------------|-----------------|----|--------------|----|--------------|
| SSSA-SVR           | 8.9670E-5       | 0.9996 | 0.001006       | 0.9947 | 3.735257    |
| ASSA-SVR           | 9.4698E-5       | 0.9995 | 0.005717       | 0.9727 | 3.989221    |
| SSA-SVR            | 9.7229E-5       | 0.9997 | 0.007108       | 0.9586 | 3.575555    |
| PSO-SVR            | 9.8874E-5       | 0.9997 | 0.027182       | 0.8950 | 4.674234    |
| GA-SVR             | 9.9263E-5       | 0.9998 | 0.034788       | 0.8772 | 6.283213    |

As can be seen from Fig.1 and table.1, the training sets of each algorithm have good effects, and there is little difference; The improved two SSA algorithms have good prediction results, and the correlation coefficient $R^2$ of sssa-svr model exceeds 0.98, and that of assa-svr model exceeds 0.97. The optimization effect of ssa-svr is the second, but the running time is the least. This is because the improved algorithm adds intra group workload, improves the search time, the prediction effect of GA and PSO test sets is relatively poor, and all indicators are at the lowest.

7. Conclusion
In order to improve the search ability of the SSA, two improved SSA are put forward, using K-means. Three strategies, adaptive search and sine-cosine search, are used to perfect the defects of SSA. Using two improved SSA algorithms to optimize the SVR model, the compressive strength of concrete can be seen that the two improved algorithms optimize the SVR model better than other algorithms, and the SSSA-SVR model is the best and stable to optimize the SVM. Therefore, the SSSA algorithm can achieve good results in optimizing SVR. Only low-dimensional data can be processed with better optimization capabilities, and high-dimensional data can be challenging.

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Reference
[1] Ouyang Chengtian,Zhu Donglin,Wang Fengqi. Application of improved sparrow search algorithm in SVM optimization[J]. Journal of Physics: Conference Series,2021,1966(1):
[2] Yin Dexin,Zhang Damin,Cai Pengchen,Qin Weina. Improved sparrow search optimization algorithm and its application [J/OL]. Computer Engineering and Science:1-8[2021-10-11].https://kns-cnki-net.webvpn.jxust.edu.cn/kcms/detail/43.1258.TP.20210930.1242.002.html.
[3] Zheng Hongqing,Feng Wenjian,Zhou Yongjian. Butterfly optimization algorithm combined with sine and cosine algorithm [J].Guangxi Science,2021,28(02):152-159.
[4] Tang Yanqiang,Chen Cheng,Cao Bo. Adaptive mutation sparrow search optimization algorithm [J/OL]. Journal of Beijing University of Aeronautics and Astronautics:1-14[2021-10-11].https://doi.org/10.13700/j.bh.1001-5965.2021.0282.
[5] Liu Kai,Dai Yongqiang. Adaptive butterfly optimization algorithm fused with mutation strategy [J/OL]. Application Research of Computers:1-9[2021-10-11].https://doi.org/10.19734/j.issn.1001-3695.2021.06.0244.
[6] Liu Lina,Nan Xinyuan,Shi Yueyuan. Improved sparrow search algorithm to solve job shop scheduling problem [J/OL]. Computer Engineering and Applications:1-7[2021-08-25].https://doi.org/10.19734/j.issn.1001-3695.2021.05.0180.
[7] Wang Shouxu,Zeng Ming. Research on Rural Highway Cost Forecast Based on SSA Optimized BP Neural Network [J]. Engineering Economy,2021,31(08):25-29.
[8] Wang Jianxin,Li Tenxu,Wang Yeru. Optimization of Food Sampling Inspection Path Based on Discrete Sparrow Search Algorithm [J]. Chinese Journal of Food Hygiene,2021,33(04):409-
9

414.

[9] Zhang Rui. Improvement and application of optimization algorithm based on sine and cosine [D]. Changchun Industrial College, 2021.

[10] Li Ailian, Quan Lingxiang, Cui Guimei, Xie Shaofeng. Sparrow search algorithm combining sine cosine and Cauchy mutation [J/OL]. Computer Engineering and Applications: 1-11 [2021-08-25]. http://kns.cnki.net/kcms/detail/11.2127.TP.20210806.0937.008.html.

[11] Guo Xiaohu. Research on Improvement of Sine and Cosine Algorithm and Its Application [D]. Hebei University of Geosciences, 2019.

[12] Gao Zixin, Bao Tenfei, Li Yangtao. Combined prediction model of crack opening of concrete dam based on MLR-SSA-GRU [J/OL]. Journal of Wuhan University (Engineering Edition): 1-10 [2021-10-11]. https://kns-cnki.net.webvpn.jxust.edu.cn/kcms/detail/42.1675.T.20211002.2210.002.html.

[13] Qian Zhongsheng, Yu Qingyuan, Song Tao, Zhu Yimin, Zhu Jie, Zhao Chang. Test case generation and reuse based on support vector machine regression model [J]. Electronic Journal, 2021, 49(07): 1386-1391.

[14] Zhao Yongqi, Zou Feng, Chen Debao, Jiang Ziqi, Kang Jiahui. Hierarchical multi-subgroup cooperative sin-cosine algorithm and its application [J]. Journal of Liaoning University of Technology (Natural Science Edition), 2020, 40(05): 342-350.

[15] Yang Ziqin, Yao Jialin, Wu Guohua, Chen Xuewei, Mao Chenghui. Integrating adaptive evolution strategy of covariance matrix and optimization algorithm of differential evolution [J].

[16] Yang Suting. Research on CET-4 Score Prediction Model Based on SVR [J]. Computer knowledge and technology, 2021, 17(18): 26-28.

[17] Wang LYU, Yuan RAO, Jun ZHU. Design and Implementation of Fresh Vegetable Sales Volume Trend Forecasting System Based on Improved SVR[J]. Agricultural Biotechnology, 2021, 10(04): 98-103.

[18] Zhang Jialong. K-means initial clustering center selection algorithm based on dissimilarity and neighborhood [J]. Computer Age, 2021(08): 57-59+62.

[19] Gong Zhen, Bu Xiaobo, Wu. Prediction model of concrete compressive strength based on PSO-SVM [J]. Concrete, 2013(12): 11-13.