frontiers | Frontiers in Earth Science

TYPE Original Research
PUBLISHED 19 January 2023
DOI 10.3389/feart.2023.1122937

OPEN ACCESS

EDITED BY
Wei Ge,
Zhengzhou University, China

REVIEWED BY
Zhen Wang,
Nanjing University of Science and Technology, China
Jie Li,
Army Engineering University of PLA, China

*CORRESPONDENCE
Peng He,
hepeng@ncwu.edu.cn

SPECIALTY SECTION
This article was submitted to Hydrosphere, a section of the journal Frontiers in Earth Science

RECEIVED 13 December 2022
ACCEPTED 03 January 2023
PUBLISHED 19 January 2023

CITATION
He P and Wu W (2023), Levy flight-improved grey wolf optimizer algorithm-based support vector regression model for dam deformation prediction.
Front. Earth Sci. 11:1122937.
doi: 10.3389/feart.2023.1122937

Levy flight-improved grey wolf optimizer algorithm-based support vector regression model for dam deformation prediction

Peng He[1]* and Wenjing Wu[2]

[1]College of Geosciences and Engineering, North China University of Water Resources and Electric Power, Zhengzhou, China, [2]School of Mechatronics Engineering, Zhongyuan University of Technology, Zhengzhou, China

Considering the strong non-linear time-varying behavior of dam deformation, a novel prediction model, called Levy flight-based grey wolf optimizer optimized support vector regression (LGWO-SVR), is proposed to forecast the displacements of hydropower dams. In the proposed model, the support vector regression is used to create the prediction model, whereas the Levy flight-based grey wolf optimizer algorithm is employed to search the penalty and kernel parameters for SVR. In this work, a multiple-arch dam was selected as a case study. To validate the proposed model, the predicted results of the model are compared with those derived from Grid Search algorithm, Particle Swarm Optimization, Grey Wolf Optimizer algorithm, and Genetic algorithm. The results indicate that the LGWO-SVR model performs well in the accuracy, stability, and rate of prediction. Therefore, LGWO-SVR model is suitable for dam engineering application.

KEYWORDS

dam deformation, support vector regression, grey wolf optimizer algorithm, levy flight, machine learning

Introduction

The safety of hyperpower dams has always been a widely-concerned issue of every country. To ensure the security of dam, dam safety monitoring model is built for monitoring the actual operation state of the dams (Li et al., 2021; Ge et al., 2020) . The deformation of a dam is commonly used to reflect the working condition during the operation period (Bui et al., 2016). Considering the non-linear and complex process of the deformation, it is difficult to forecast the dam behavior with high accuracy (Chen et al., 2018).

In recent years, various machine learning methods, such as artificial neural network, support vector machine, and random forest method, have been applied to establish the prediction models of dam deformation (Salazar F et al., 2017). The most widely used method is artificial neural networks (ANNs). However, an artificial neural network is more likely to fall into the situation that the trained ANN over-fits training samples, which reduces the accuracy of predicted dam deformation.

Support vector regression (SVR) has always been a hotspot in civil engineering to solve regression prediction (Su et al., 2015). SVR has distinctive superiority in solving non-linear problems with few samples and high dimensions. The prediction accuracy of SVR is influenced by the values of the penalty and kernel parameters in SVR. Therefore, a number of swarm intelligence algorithms were presented to optimize the parameters, including the Grid Search algorithm (GS), Particle Swarm Optimization algorithm (PSO), Cuckoo Search algorithm (CS), Genetic Algorithm (GA), *etc.* Su et al. (2018) employed the Particle Optimization algorithm (PSO) to seek the best parameter set for SVR in predicting dam deformation. Ranković et al. (2014) proposed an SVR-based model for forecasting the dam deformation. In Rankovic's model, the parameters of SVR are specified with the trial-and-error method. Shu et al (2021) proposed a variational autoencoder-based model for dam displacement prediction. Li et al (2019) proposed a novel distributed time series evolution model for predicting the dam deformation. Meng et al. (2018) combined the Ant Colony Optimization algorithm (ACO) with SVR to forecast the price of stock. Kaltich et al. (2015) presented a wavelet genetic algorithm-support vector regression (GA-SVR) to forecast monthly river flows. Xue et al. (2018) proposed the Artificial Bee Colony algorithm (ABC) for global optimization to obtain the optimal solutions of several benchmark functions. In conclusion, the possible optimal solution can be obtained through these algorithms, but these algorithms are more likely to fall into the local optimal solutions and their convergence rates are very slow. Considering the lower speed and precision of these algorithms, a novel type of swarm intelligence algorithm called the Grey Wolf Optimizer (GWO) algorithm is introduced in this paper.

The Grey Wolf Optimizer algorithm has received much attention and been widely used in many fields such as optimal reactive power scheduling, multiple input and output problems, and truss structures with motive power restrict (Faris H et al., 2017). The GWO algorithm is easy to implement and has fewer control parameters. Numerical comparisons showed that the GWO algorithm could present a higher performance than other swarm intelligence algorithms (Zhang and Zhou, 2015). The search scope become more and more smaller with the increase of iterations in the GWO algorithm, which increase the possibility of falling into a local optimum. To expand the scope of the search, the Levy flight is combined with the GWO algorithm to optimize the parameters. The Levy flight is a random process that is inspired by the Levy distribution (Viswanathan et al., 1996). Application of the Levy flight can result in a more effective search because of the use of the long jumps. The Levy flight can reduce the possibility of falling into a local optimum, taking into account the short-range exploratory hopping and occasional long-distance walking simultaneously.

In this paper, the Levy flight-based Grey Wolf Optimizer (LGWO) algorithm is presented to optimize support vector regression model for forecasting dam deformation. Historical data of the water pressure, temperature, and time-varying effect values of a dam are taken as input variables and the model is constructed to forecast the deformation. To validate the performance of the LGWO algorithm, a comprehensive comparison is carried out among the prediction capability of some other swarm intelligence algorithms.

The rest of the paper is organized as follows: Section 2 presents a brief introduction to the Levy flight-based Grey Wolf Optimizer algorithm and the Support Vector Regression model, describes the framework of the LGWO-SVR model, and presents the criteria of prediction performance. Section 3 presents a description of a case study, the calculation of the input effects, and the initial parameters of each algorithm. The comprehensive comparison among those swarm intelligence algorithms and the prediction results of the LGWO-SVR model are also showed in Section 3. Finally, the conclusion for the current work is given in Section 4.

LGWO-SVR model

There are many factors affecting dam deformation, such as water pressure, seepage coupling, joint fissure, concrete temperature, etc (Wei et al., 2019). Limited by current monitoring technology and analysis theory, the prediction for dam deformation is complex. It is generally accepted that the displacements are composed of water pressure component, temperature component, and time-varying component. The relationships between these components and their relevant factors are non-linear. For example, water pressure component is the polynomials of the water depth. The prediction of dam deformation is a non-linear problem with high dimensions. As mentioned above, the SVR has distinctive superiority in solving non-linear problems with few samples and high dimensions. Therefore, it is suitable for the SVR to construct a prediction model.

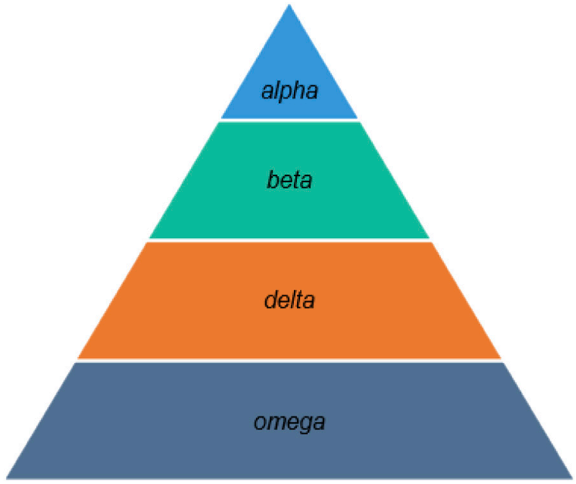

FIGURE 1
Social hierarchy of grey wolves (dominance decreases from top to bottom).

Support vector regression

The support vector regression (SVR) is data-based prediction model improved by the support vector classification. The basic idea of SVR is to find an optimal classification surface to minimize the error of all training samples from the optimal classification surface (Li et al., 2018). Suppose that there is a training sample set $\{(x_i; y_i)\}(i=1,2,\ldots;n)$. x_i denotes the input variable vector of the i th training sample, y_i ($y_i \in R$) represents the corresponding output value, and n is the number of sample points.

The goal of SVR is to find a function relationship $f(x)$ between the input vector x_i and the output vector y_i under the premise that the relationship between input and output variables is unknown. The function can be expressed as a linear relationship as follows:

$$f(x) = w\phi(x) + b \tag{1}$$

where w represents the weight coefficient matrix, b represents the value of offsets, and $\phi(x)$ is a non-linear mapping function which is used to transform the complex non-linear problem in to a simple linear problem.

Based on the principle of structural risk minimization, the function $f(x)$ should loosely fit training data and avoid over-fitting problem by minimizing the norm of w (i.e., $\|w\|$). To cope with infeasible constrains, two slack variables ξ_i and ξ_i^* are introduced.

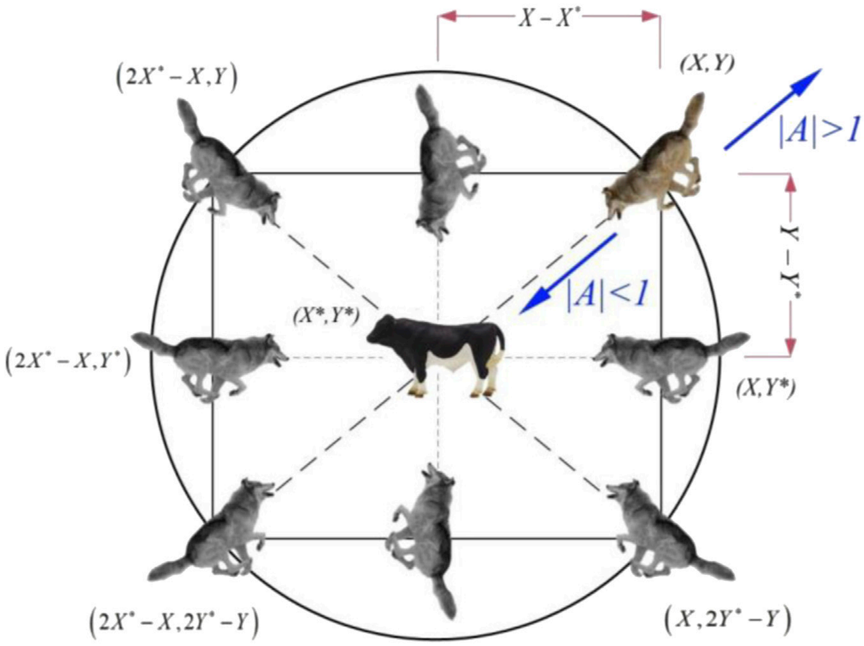

FIGURE 2
Position vectors and the possible next locations of a grey wolf.

Then the seeking process of minimizing w can be converted to solving the convex optimization problem:

$$\begin{cases} \min \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{m}(\xi_i + \xi_i^*) \\ s.t. \begin{cases} y_i - w\phi(x) - b \le \varepsilon + \xi_i \\ -y_i + w\phi(x) + b \le \varepsilon + \xi_i^*, i = 1, 2, \cdots m \\ \xi_i \ge 0, \xi_i^* \ge 0 \end{cases} \end{cases} \tag{2}$$

where ε is the insensitive loss function which represents the error requirements for the regression function, and $C\,(C > 0)$ is the penalty factor. A larger C indicates that a larger penalty will be exerted on the samples when the training error is bigger than ε.

The convex optimization problem can be converted to solving the extremum of Lagrangian function L through the Lagrange multiplier method.

$$\begin{aligned} L(w, b, \xi_i, \xi_i^*, \alpha_i, \alpha_i^*, \eta_i, \eta_i^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*) \\ -\sum_{i=1}^{n}\alpha_i(\xi_i + \varepsilon - y_i + w\phi(x_i) + b) \\ -\sum_{i=1}^{n}\alpha_i^*(\xi_i^* + \varepsilon + yi - w\phi(x_i) - b) \\ -\sum_{i=1}^{n}(\eta_i\xi_i + \eta_i^*\xi_i^*) \end{aligned} \tag{3}$$

where α_i, α_i^*, η_i, and η_i^* are the Lagrangian multipliers, which satisfy the positivity constraints.

According to the Karush-Kuhn-Tucher (KKT) condition which describes the necessary and sufficient conditions to meet the optimal solution, the derivatives of L about the original variable must be 0 to obtain optimal results (Smola and Scholkopf, 2004).

$$\frac{\partial L}{\partial b} = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*) = 0, 0 \le \alpha_i, \alpha_i^* \le C \tag{4}$$

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\varphi(x_i) = 0 \Rightarrow w = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)\varphi(x_i) \tag{5}$$

$$\frac{\partial L}{\partial \xi_I^*} = C - \alpha_i^* - \eta_i^* = 0 \Rightarrow C = \alpha_i^* + \eta_i^* \tag{6}$$

According to Eq. 5, the regression function of the SVR model can be transformed as follows.

$$f(x) = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)(\phi(x_i)\cdot\phi(x)) + b = \sum_{i=1}^{n}(\alpha_i - \alpha_i^*)K(x, x_i) + b \tag{7}$$

where $K(x, x_i)$ represents the kernel function.

When the SVR is used to solve the non-linear regression problem in practice, the non-linear problem is mapped to a high-dimensional space and the linear function is constructed in this space by selecting an appropriate kernel function. The selection of kernel function has a significant influence on the performance of the SVR because different kernel function is suitable for different data types (Huang et al., 2012). A radial basis kernel function is more favored than other kernel functions due to its facilitating implementation and strong mapping performance (Rasmussen, 2003). The expression of a radial basis kernel function is shown in Eq. 8.

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \tag{8}$$

where σ denotes the parameter related to the width of kernel in statistics.

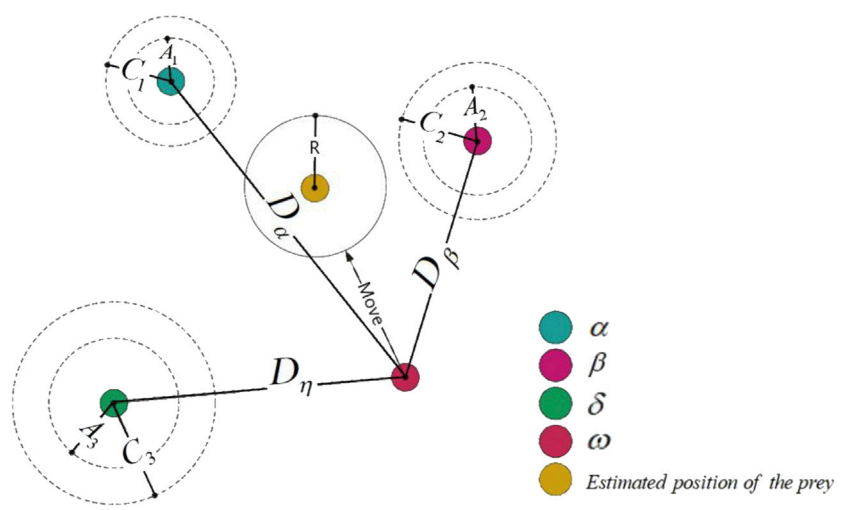

FIGURE 3
Location updating process of grey wolves in 2D space.

Using the Lagrangian multiplier method, duality principle, and the kernel function, the problem is transformed into a quadratic programming optimization one.

$$\max\left\{-\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)exp\left(-\frac{\|x_i-x_j\|^2}{2\sigma^2}\right)-\varepsilon\sum_{i=1}^{n}(\alpha_i+\alpha_i^*)+\sum_{i=1}^{n}y_i(\alpha_i-\alpha_i^*)\right\}$$
$$\text{subject to}\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)=0\quad\text{and}\ \alpha_i,\alpha_i^*\in[0,C] \tag{9}$$

Obtaining the Lagrange multiplier α_i and α_i^* from the above quadratic optimization problem, the regression function of support vector machine can be expressed as Eq. 10.

$$f(x)=\sum_{i=1}^{n}(\alpha_i-\alpha_i^*)\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right)+b \tag{10}$$

where α_i and α_i^* are the Lagrange multipliers, and σ denotes the parameter related to the width of kernel in statistics.

There are two essential parameters (the penalty parameter C and kernel parameter σ) in a SVR. The penalty parameter C controls the trade-off between the complexity of the function and the frequency in which errors are allowed. The parameter σ affects the mapping transformation of the input data to the feature space and controls the complexity of the model. Thus, it is important to select suitable parameters in the SVR.

A levy flight-based grey wolf optimizer (LGWO)

As mentioned above, the penalty parameter C and the kernel parameter σ are essential in a SVR. Many swarm intelligence algorithms mentioned above were presented to optimize those two parameters. However, these algorithms are more likely to fall into local optimum solutions. To cope with the problem, a novel algorithm called Levy flight-based Grey Wolf Optimizer (LGWO) is introduced to select the suitable parameters for the SVR.

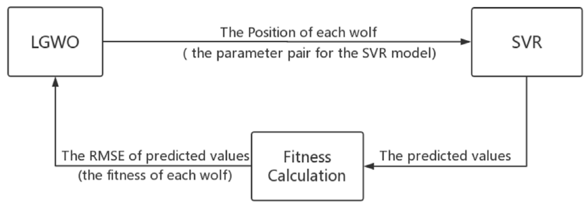

FIGURE 4
The process of training SVR using LGWO.

GWO is a swarm intelligence meta-heuristic algorithm given by Mirjalili et al. (2014). The inspiration of the GWO algorithm is based on the social hierarchy and hunting strategy of grey wolves in nature (Searemi et al., 2014). In each group of grey wolves, there is a very strict social dominant hierarchy shown in Figure 1.

To simulate the social hierarchy of grey wolves, four categories of wolves are defined--alpha (α), beta (β), delta (δ), and omega (ω). In the iterative calculation process, the first three best solutions are considered as alpha, beta, and delta, respectively. The rest of the candidate solutions are called omega. The wolves need to encircle the first three optimal solutions (alpha, beta, and delta) to find better solution for the problem (Mirjalili et al., 2014), which is modelled as:

$$\vec{D}=\left|\vec{C}\cdot\vec{X}_P(t)-\vec{X}(t)\right| \tag{11}$$

$$\vec{X}(t+1)=\vec{X}_P(t)-\vec{A}\cdot\vec{D} \tag{12}$$

where t denotes the current iteration, $\vec{X}_p$ denotes the position vector of the prey, $\vec{X}$ represents the position vector of a grey wolf, and $\vec{A}$, $\vec{C}$ are the random vectors.

The random vectors $\vec{A}$ and $\vec{C}$ are formulated as:

$$\vec{C}=2\vec{r}_2,\vec{A}=2\vec{a}g\vec{r}_1-\vec{a} \tag{13}$$

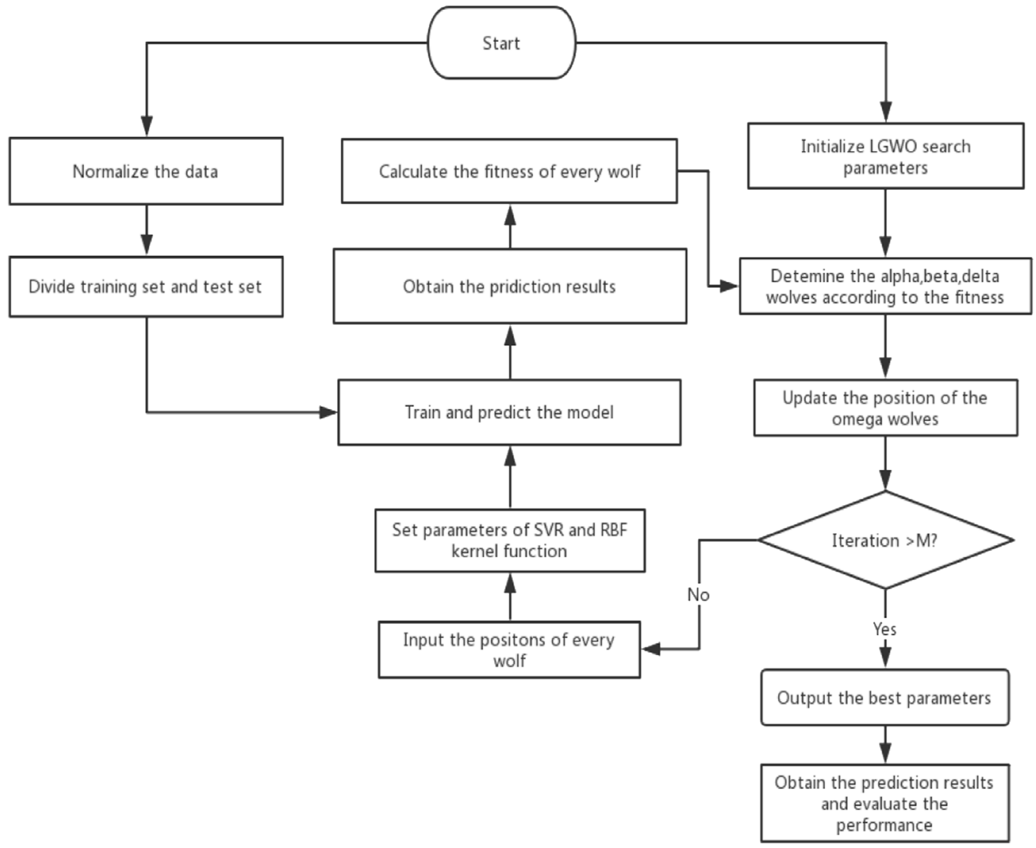

FIGURE 5
Structure of the proposed LGWO-SVR model.

where a is gradually linearly decreased from 2 to 0, and $\vec{r}_1$, Combination forecast model for concrete dam displacement considering residual correction $\vec{r}_2$ are random vectors in $[0, 1]$.

Different mathematical operators are defined in Eqs 11–13, which can be summarized as follows:

$$\vec{D}g\vec{B} = (d_1b_1, d_2b_2, \mathrm{L}, d_nb_n)$$

$$\left|\vec{E}\right| = (|e_1|, |e_2|, \mathrm{L}, |e_n|)$$

where $\vec{D}$, $\vec{B}$, and $\vec{E}$ are N-dimensional vectors. $\vec{D} = (d_1, d_2, \cdots, d_n)$, $\vec{B} = (b_1, b_2, \cdots, b_n)$, and $\vec{E} = (e_1, e_2, \cdots, e_n)$.

Figure 2 shows how a grey wolf updates its position (X, Y) according to the position of the prey (X^*, Y^*). In the process of encircling prey, the grey wolf can reach different places around the best agent by adjusting the parameter values of A and C in Eqs 11, 12.

To simulate the hunting behavior of the grey wolves, the alpha, beta, and delta wolves in the GWO algorithm are three best solutions obtained so far. The omega wolves are obliged to update their positions according to the positions of the above best wolves. The hunting process can be mathematically described (Song et al., 2015):

$$\vec{D}_\alpha = \left|\vec{C}_1 g\vec{X}_\alpha - \vec{X}\right|, \vec{D}_\beta = \left|\vec{C}_2 g\vec{X}_\beta - \vec{X}\right|, \vec{D}_\delta = \left|\vec{C}_3 g\vec{X}_\delta - \vec{X}\right| \tag{14}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 g\vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 g\vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 g\vec{D}_\delta \tag{15}$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3} \tag{16}$$

where C_1, C_2, C_3, A_1, A_2, and A_3 represent the random vectors, X_α, X_β, and X_δ represent the positions of the alpha, beta, and delta wolves respectively, t represents the number of iteration, and $\overset{r}{X}$ is the position of current solution.

As showed in Figure 3, a grey wolf can update its position according to the positions of alpha, beta, and delta wolves in a 2D search space. The final possible position of the prey is distributed in a circle determined by the positions of alpha, beta, and delta in the search space. The hunting process can be summarized that the position of the prey is estimated by the best three wolves, whereas the other wolves update their positions randomly around the prey.

When the grey wolves start to attack the prey, the encirclement of wolves became smaller and smaller. The GWO algorithm are more likely to fall into local optimum solutions under the small search encirclement (Mirjalili et al., 2015). Considering the small encirclement, the Levy flight is introduced to increase the ability of global and local search simultaneously.

The Levy flight is a category of random search process (Amirsadri et al., 2017). In this method, the short-range exploratory hopping and occasional long-distance walking are combined to result in a more effective search. The hopping behavior ensures that the search agents can search the small areas carefully, whereas the long-distance walking behavior ensures that the search agents can enter into another areas

FIGURE 6
Layout of the multiple-arch dam.

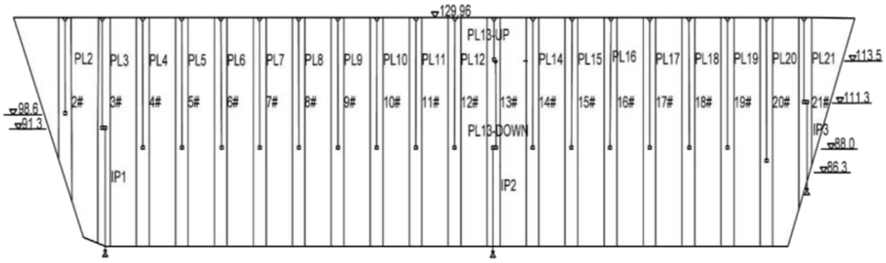

FIGURE 7
Pendulum systems for monitoring horizontal displacement.

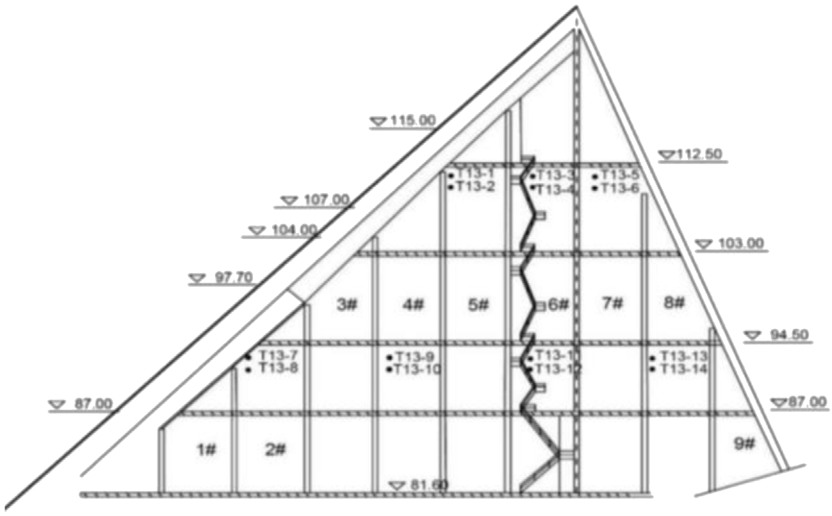

FIGURE 8
Thermometers installed in the dam section 13.

and search a wider range. The jump size in the Levy flight follows the Levy probability distribution function (Yang and Deb, 2009). Considering the difficulty of calculating the search path, a simple mathematical definition of the Levy distribution is described:

$$s = u/|v|^{\frac{1}{\beta}} \tag{17}$$

where s is the random step size obeying the Levy distribution, and u, v are the random numbers produced by normal distribution.

$$u : N(0, \sigma^2), v : N(0, 1) \tag{18}$$

with

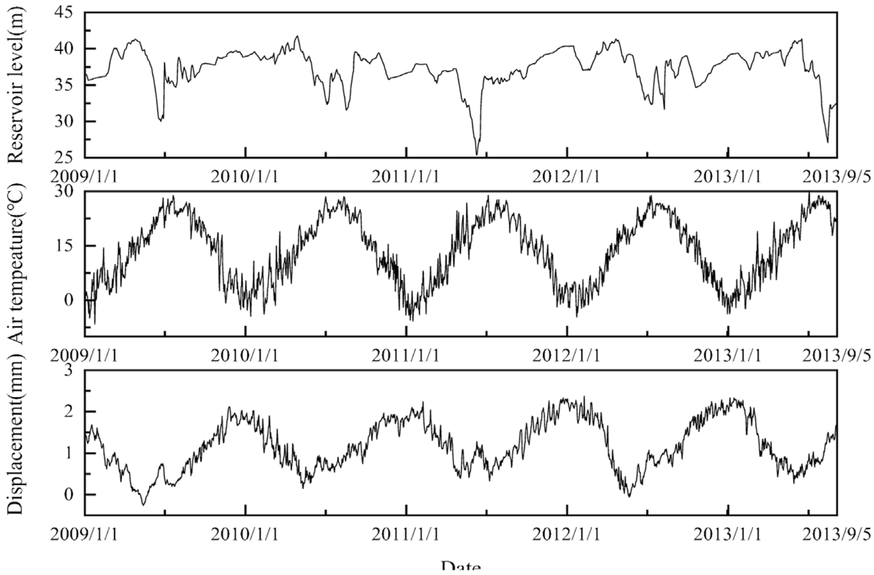

FIGURE 9
Reservoir level, air temperature, and displacements recorded in the dam section 13.

$$\sigma = \left\{ \frac{f(1+\beta) g \sin\left(\frac{\pi\beta}{2}\right)}{\beta g f\left(0.5+\frac{\beta}{2}\right) g2^{(\beta/2-0.5)}} \right\}^{1/\beta} \tag{19}$$

where $f(x)$ is the standard gamma function, and the range of β is from 0 to 3.

In this study, a hybrid optimization algorithm which combines the GWO algorithm with the Levy flight is presented. In the proposed algorithm, all the wolves except the three leading wolves update their positions through the Levy flight. Therefore, the following equations can be used to update the position.

$$\vec{X}(t+1)_{LGWO} = \vec{X}(t+1) + S \tag{20}$$

where S is the step size determined by Eqs 17–19, $\vec{X}_{LGWO}(t+1)$ is the updated position of the wolf after the Levy flight, and $\vec{X}(t+1)$ is the updated position of the wolf without the Levy flight calculated by Eqs 14–16.

LGWO for parameter determination for SVR

As mentioned above, the penalty parameter C and the kernel function parameter σ in a SVR have a significant influence on the prediction performance. The LGWO algorithm is introduced to obtain the best series of parameters for the SVR. Therefore, the position of each wolf in the LGWO algorithm represents a parameter pair (C, σ) and the root mean squared error between the measured and predicted values is served as the fitness of each wolf.

Figure 4 shows the overall process of training the SVR using the LGWO algorithm at each iteration. At the beginning, the positions of wolves are obtained from the last iteration and served as the parameters of SVR. After giving the position of each wolf in SVR successively and training SVR, the predicted values of the testing sample are generated in SVR. Then the root mean squared error (RMSE) as the fitness of each wolf is given to the LGWO algorithm from SVR. The positions of the wolves are updated in the LGWO algorithm according to the fitness given by SVR. Finally, the best parameter pair (C, σ) is obtained from the

TABLE 1 Initial parameters.

Algorithm	Parameter	Value
LGWO	Population size	10
	$\vec{a}$	Linearly decreased from 2 to 0
	Max iteration	100
	Stopping criteria	Max iteration
	β	1.5
GWO	Population size	10
	$\vec{a}$	Linearly decreased from 2 to 0
	Max iteration	100
	Stopping criteria	Max iteration
PSO	Population size	10
	C_1, C_2	0.5,0.5
	W	0.8
	Max iteration	40
	Stopping criteria	Max iteration
GA	Population size	10
	C_1, C_2	0.6,0.001
	Max iteration	40
	Stopping criteria	Max iteration

TABLE 2 Experimental results of every algorithm.

Algorithm	RMSE		RAE		R^2	
	Averaged	Std dev	Averaged	Std dev	Averaged	Std dev
LGWO	0.1021	1.8E-05	0.0830	2.0E-05	0.9594	4.6E-05
GWO	0.1051	3.9E-03	0.0856	3.3E-03	0.9564	4.5E-03
PSO	0.2035	0.0782	0.1713	0.0685	0.7661	0.1411
GS	0.2755	0.0432	0.2378	0.0441	0.6036	0.1276
GA	0.3036	0.0681	0.2708	0.0703	0.4935	0.2234

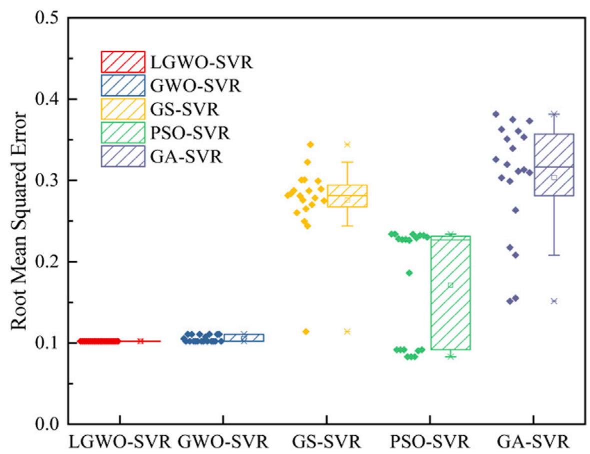

FIGURE 10
The distribution of RMSE at each run of each algorithm.

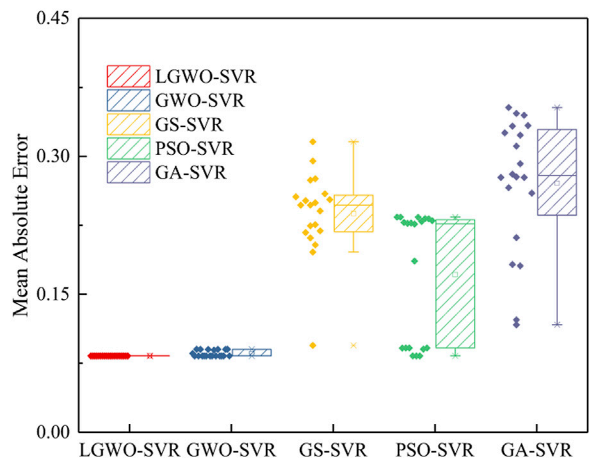

FIGURE 12
The distribution of MAE at each run of each algorithm.

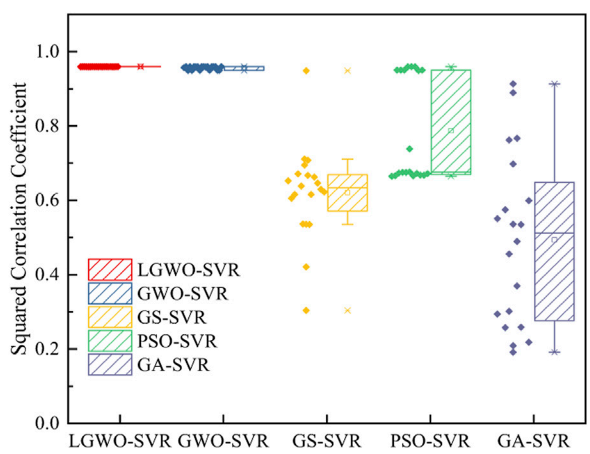

FIGURE 11
The distribution of R2 at each run of each algorithm.

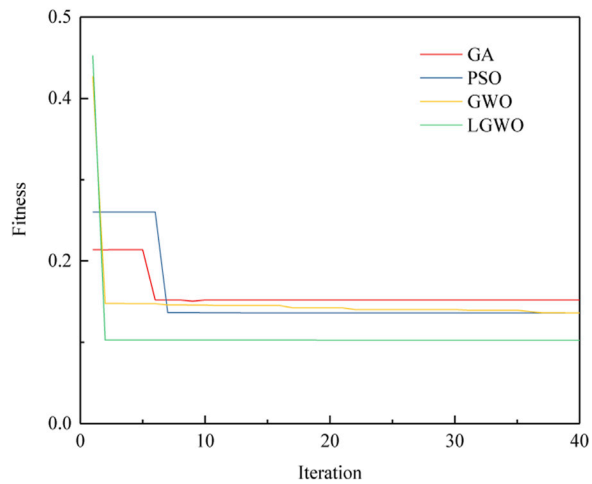

FIGURE 13
Convergence curves of the five algorithms over 20 independent runs.

LGWO algorithm and the predicted value with highest prediction accuracy is generated in SVR after reaching the maximum iteration.

In this paper, a novel hybrid model composed of the Levy flight-based grey wolf optimizer (LGWO) and support vector regression (SVR) was proposed and applied to make prediction for dam

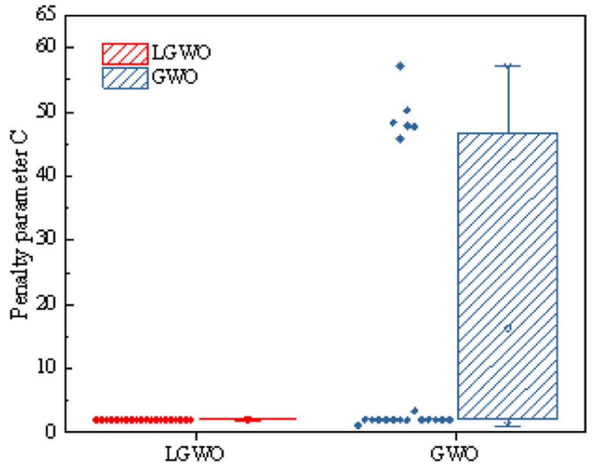

FIGURE 14
The distribution of parameter C for 20 independent runs of the LGWO and GWO algorithms.

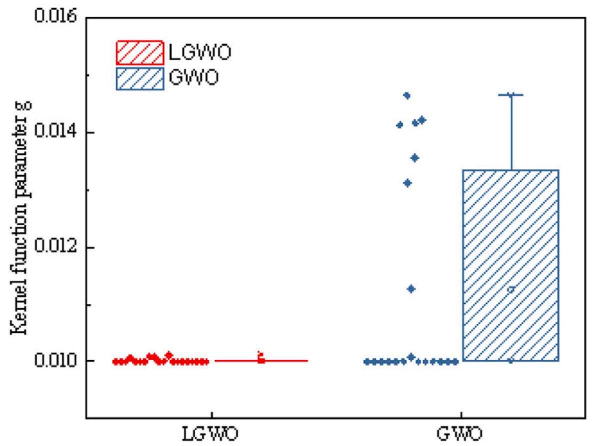

FIGURE 15
The distribution of parameter σ at 20 independent runs of the LGWO and GWO algorithms.

deformation. The structure of the proposed hybrid method for dam deformation prediction is shown in Figure 5. To avoid calculation error caused by numerical differences, the data is normalized and all the samples are divided into the training and testing samples. Main steps are as followed.

Step 1: Normalize the parameters of the LGWO-SVR model.

Step 2: Initialize the population of the wolf pack.

Step 3: Enter the position of each wolf to the SVR model and obtain the fitness of each wolf.

Step 4: Select the alpha, beta, and delta wolves in the wolf pack.

Step 5: Update the positions of the omega wolves.

Step 6: If the maximum iteration number reaches, the iteration is terminated and the position of the alpha wolf is outputted. Otherwise, repeat steps 3–6;

Step 7: Train the SVR model according to the outputted parameters and obtain the prediction values.

Criteria of prediction performance evaluation

To evaluate the performance of the proposed model, three widely used quantitative evaluation indicators are introduced. The specific expression of these indicators is shown as follows:

Squared correlation coefficient (R^2)

$$R^2 = \frac{\left[n\sum_{i=1}^{n}\hat{y}_i y_i - \sum_{i=1}^{n}\hat{y}_i\sum_{i=1}^{n}y_i\right]^2}{\left[n\sum_{i=1}^{n}\hat{y}_i^2 - \left(\sum_{i=1}^{n}y_i^2\right)^2\right]\left[n\left(\sum_{i=1}^{n}\hat{y}_i^2\right) - \left(\sum_{i=1}^{n}\hat{y}_i\right)^2\right]} \tag{21}$$

Mean absolute error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{22}$$

Root mean squared error (RMSE)

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{23}$$

where n is the number of testing samples, $\hat{y}_i$ is the predicted value of the i th testing sample, and y_i is the measured value of the i th testing sample.

Case study

General description of the project

The project used in this paper is situated on the Luo River (a tributary of the Huaihe River) in Anhui province, China. It is a multiple-arch dam consisting of 20 sections and 21 arches showed in Figure 6. The total height of the dam is 75.9 m, and the total length of the dam is 510 m. To understand the real-time working status of the dam during operation, the dam is installed with pendulum monitoring system. The aim is to monitor and assess the horizontal displacements of the dam. A total of 21 pendulum systems are installed in the arches. The pendulum monitoring system consists of 20 pendulum lines (PL) and three inverted pendulum lines (IP). The distribution of the pendulums is showed in Figure 7. The raw data was recorded by manual and automated equipment every day.

At the same time, some environmental data are also monitored, such as reservoir level, air temperature, water temperature. There are 57 thermometers embedded in the dam body, which are used to measure air, water, and concrete temperatures. In this study, the dam section 13 is selected for testing the model. The thermometer distribution of the dam section 13 is showed in Figure 8.

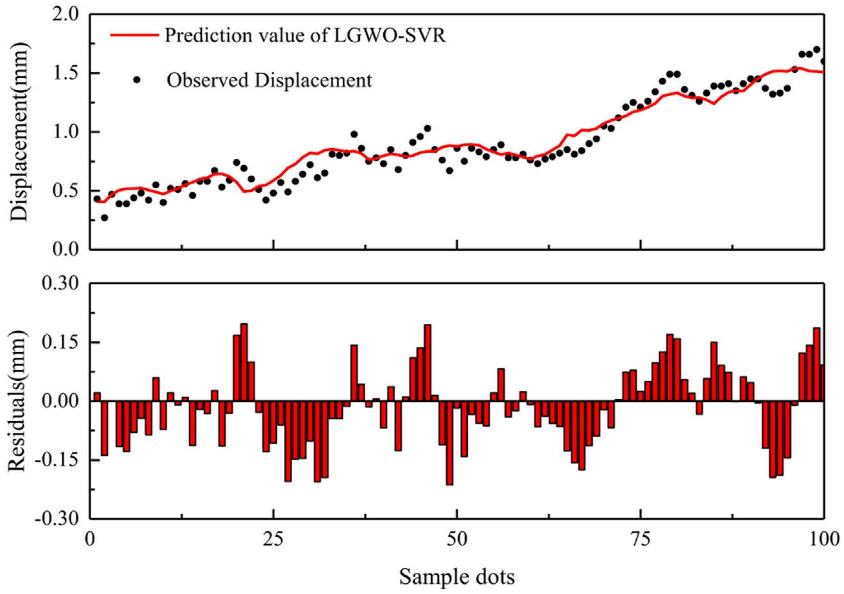

FIGURE 16
Measured and predicted displacements from the LGWO-SVR model.

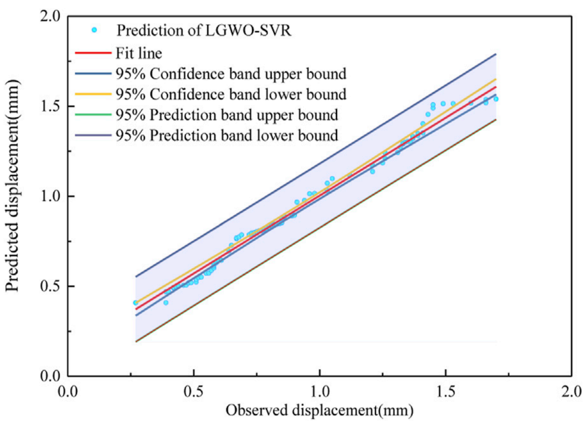

FIGURE 17
Linear regression analysis between the measured and the predicted values.

Input variables selection and data processing

In this study, the environmental monitoring data and displacements of the dam section 13 are used. Time series with 1700 data points from January 2009 to September 2013 are selected. The time series are divided into training and testing samples. The training time series are from January 2009 to June 2013. The testing time series are from June 2013 to September 2013. The amounts of training and testing samples are 1,000 and 260. The time series of air temperature, reservoir level, and displacements are presented in Figure 9.

Dam deformation is mainly influenced by hydraulic effect, thermal effect, and time-varying effect (Wei et al., 2019). For the hydraulic effect, it is usually considered as a reversible effect and can be represented by the polynomials(H^4; H^3; H^2; H) of the reservoir level. To consider the thermal effect, the measured temperatures including air, water, dam foundation, and concrete temperatures(T_{air}; T_{water}; $T_{foundation}$;; $T_{conctrete}$) are used. The time-varying effect represents the irreversible deformation of dam over the time effect. The effect could be represented by the combination of θ, $\ln(1+\theta)$, and $\theta/(\theta+1)$ where $\theta = t/100$ and t is the cumulative days from current data to initial monitoring date. Therefore, a total of 11variables are used as the input variables to construct the model and the displacements are the outputs.

Training the SVR model using LGWO

As mentioned above, there are two parameters (the penalty parameter C and kernel function parameter σ) in the SVR. The range of values of C and σ is [0.01,100] in SVR. In the LGWO algorithm, the number of the grey wolves is 20 and the maximum iteration is 100.

To describe the prediction performance of the LGWO-SVR model, four other algorithms are combined with SVR to predict the displacements: GS, PSO, GWO, and GA. Table 1 shows the initial parameters of these algorithms. To test the stability for each algorithm, 20 independent runs are carried out.

Results and discussion

The results from all the algorithms are presented in Table 2. The results are averaged over 20 independent runs. The Averaged and Std dev represent the mean evaluation indicators and standard deviation, respectively. As showed in Table 2, the squared correlation coefficients of the LGWO algorithm are 0.9594, which are higher than other four algorithms. In addition, the MAE and RMSE of the LGWO algorithm are lower than the other four algorithms. It indicates that the LGWO algorithm performs better in the prediction accuracy.

To assess the solution stability of the LGWO algorithm, the distributions of evaluation indicators for the LGWO algorithm ais drew in Figures 10–12 with those for four other algorithms. It can be seen that the RMSE, MAE, R^2 of the LGWO algorithm are concentrated near 0.1, 0.8, and 0.96, respectively. However, the evaluation indicators of the other four algorithms are decentralized. The LGWO algorithm can obtain the parameter pair with the higher accuracy at each run. However, only one series of parameters is obtained in the GA and GS algorithm and eight series of parameters are obtained in the PSO algorithm at each independent 20 runs. It indicates that the LGWO algorithms perform well in the prediction stability.

Figure 13 shows the convergence curves of the five algorithms. The LGWO algorithm can reach the best solution at the third iteration although the initial fitness of the LGWO algorithm is much higher than the other algorithms, which indicates that the LGWO algorithm performs well in solution rate.

The above evaluations show that the LGWO algorithm performs better than the other algorithm in prediction accuracy, solution stability, and solution rate.

Considering the similar performance of the LGWO and GWO algorithms, the results of the 20 independent runs are presented in Figures 14, 15. The best series of the parameters is concentrated near (2.00,0.01) in the LGWO algorithm and the fitness of the result is all near 0.9595. However, the series of the parameter obtained from the GWO algorithm is decentralized and the fitness of six runs in 20 independent ones is about 0.9495. From this aspect, the GWO algorithm is more likely to fall into a local optimum and the LGWO algorithm can reduce the possibility of falling into a local optimum.

To further validate the performances of the LGWO-SVR model, the predicted displacements of the LGWO-SVR model and the measured displacements are shown in Figure 16. The best series of the parameters ($C = 2.029, \sigma = 0.010$) were found using the LGWO-SVR model. It can be seen from the figure that the LGWO-SVR model has better performance in prediction accuracy and reflect the variation of the dam displacements in a short time period. Figure 17 shows the linear fitting results of the measured and predicted displacements of the LGWO-SVR model. From the figure, the predicted values are within the 95% prediction band, which indicates the predicted results are very close to the actual values.

Conclusion

In this paper, a Levy flight-based grey wolf optimizer algorithm is applied into support vector regression for predicting dam deformation. In the proposed approach, the recently popular GWO algorithm was employed as the swarm intelligence algorithm to obtain the best parameters of the SVR model. Considering the possibility of falling into the local optimum, the Levy flight-based grey wolf optimizer was proposed to increase the chance of searching the potential global optimal solution. For verification, the results of the LGWO-SVR model were compared with four other swarm intelligence algorithms (PSO, GA, GS, and GWO). The prediction accuracy of the model is accessed by using MAE, RMSE, and R^2. The stability of the model can be seen from the distribution of the MAE, RMSE, and R^2 for 20 independent runs. The results showed that the LGWO-SVR model have higher prediction accuracy, stability, and solution rate than the other swarm intelligence algorithms, and the LGWO algorithm can obtain the global optimum of the SVR model for each run. This indicates that the LGWO algorithm is a good swarm intelligence algorithm to obtain the optimal parameter of SVR. Generally, the major contribution of this study of the dam deformation prediction are highlighted as follows:

(1) The LGWO algorithm was used to obtain the best series of the parameter in the SVR model and the results showed that the LGWO algorithm have the capability to obtain the global optimum accurately and swiftly.
(2) The dam deformation predicted by the LGWO-SVR model were compared with other swarm intelligence algorithms and the result showed that the LGWO-SVR model could reach better fitting accuracy and have lower residuals.
(3) The good performance of the LGWO-SVR model indicates that the Levy flight can reduce the possibility of falling into the local optimum.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

Author contributions

Conceptualization: PH; methodology: PH; validation: PH and WW; formal analysis: PH and WW; data curation: PH; writing—original draft preparation, PH; writing—review and editing, PH and WW; funding acquisition, PH.

Funding

This work was supported by the High-level Talent Start-up Research Foundation of North China University of Water Resources and Electric Power (201810001).

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

References

Amirsadri, S., Mousavirad, S. J., and Ebrahimpour-Komleh, H. (2017). A Levy flight-based grey wolf optimizer combined with back-propagation algorithm for neural network training. *Neural Comput. Appl.* 30 (12), 3707–3720. doi:10.1007/s00521-017-2952-5

Bui, K-T. T., Tien Bui, D., Zou, J., Van Doan, C., and Revhaug, I. (2016). A novel hybrid artificial intelligent approach based on neural fuzzy inference model and particle swarm optimization for horizontal displacement modeling of hydropower dam. *Neural Comput. Appl.* 29 (12), 1495–1506. doi:10.1007/s00521-016-2666-0

Chen, B., Hu, T., Huang, Z., and Fang, C. (2018). A spatio-temporal clustering and diagnosis method for concrete arch dams using deformation monitoring data. *Struct. Health Monit.* 18, 1355–1371. doi:10.1177/1475921718797949

Faris, H., Aljarah, I., Al-Betar, M. A., and Mirjalili, S. (2017). Grey wolf optimizer: A review of recent variants and applications. *Neural Comput. Appl.* 30 (2), 413–435. doi:10.1007/s00521-017-3272-5

Ge, W., Li, Z., Li, W., Wu, M., Li, J., and Pan, Y. (2020). Risk evaluation of dam-break environmental impacts based on the set pair analysis and cloud model [J]. *Nat. Hazards* 104, 1641–1653. doi:10.1007/s11069-020-04237-9

Huang, G., Zhou, H., Ding, X., and Zhang, R. (2012). Extreme learning machine for regression and multiclass classification. *IEEE Trans. Syst. Man, Cybern. Part B Cybern.* 42 (2), 513–529. doi:10.1109/tsmcb.2011.2168604

Kaltich, A. M. (2015). Wavelet genetic algorithm-support vector regression (wavelet GA-SVR) for monthly flow forecasting. *Water Resour. Manag.* 29 (4), 1283–1293. doi:10.1007/s11269-014-0873-y

Li, M., Shen, Y., Ren, Q., and Li, H. (2019). A new distributed time series evolution prediction model for dam deformation based on constituent elements. *Adv. Eng. Inf.* 39, 41–52. doi:10.1016/j.aei.2018.11.006

Li, S., Fang, H., and Liu, X. (2018). Parameter optimization of support vector regression based on sine cosine algorithm. *Expert Syst. Appl.* 91, 63–77. doi:10.1016/j.eswa.2017.08.038

Li, Z., Zhang, Y., Wang, J., Ge, W., Li, W., Song, H., et al. (2021). Impact evaluation of geomorphic changes caused by extreme floods on inundation area considering geomorphic variations and land use types [J]. *Sci. Total Environ.* 754, 142424. doi:10.1016/j.scitotenv.2020.142424

Meng, Q. N., and Xu, X. (2018). Price forecasting using an ACO-based support vector regression ensemble in cloud manufacturing. *Comput. Industrial Eng.* 125, 171–177. doi:10.1016/j.cie.2018.08.026

Mirjalili, S. (2015). How effective is the Grey Wolf optimizer in training multi-layer perceptrons. *Appl. Intell.* 43 (1), 150–161. doi:10.1007/s10489-014-0645-7

Mirjalili, S., Mirjalili, S. M., and Lewis, A. (2014). Grey wolf optimizer. *Adv. Eng. Softw.* 69, 46–61. doi:10.1016/j.advengsoft.2013.12.007

Ranković, V., Grujović, N., Divac, D., and Milivojević, N. (2014). Development of support vector regression identification model for prediction of dam structural behaviour. *Struct. Saf.* 48, 33–39. doi:10.1016/j.strusafe.2014.02.004

Rasmussen, C. E. (2003). "Gaussian processes in machine learning," in *Lecture notes in computer science*, 63–71.

Salazar, F., Moran, R., Toledo, M. A., and Onate, E. (2017). Data-based models for the prediction of dam behaviour: A review and some methodological considerations. *Archives Comput. Methods Eng.* 24 (1), 1–21. doi:10.1007/s11831-015-9157-9

Searemi, S., Mirjalili, S. Z., and Mirjalili, S. M. (2014). Evolutionary population dynamics and grey wolf optimizer. *Neural Comput. Appl.* 26 (5), 1257–1263. doi:10.1007/s00521-014-1806-7

Shu, X., Bao, T., Li, Y., Gong, J., and Zhang, K. (2021). VAE-TALSTM: A temporal attention and variational autoencoder-based long short-term memory framework for dam displacement prediction. *Eng. Comput.* 38, 3497–3512. doi:10.1007/s00366-021-01362-2

Smola, A. J., and Scholkopf, B. (2004). A tutorial on support vector regression. *Statistics Comput.* 14 (3), 199–222. doi:10.1023/b:stco.0000035301.49549.88

Song, X., Tang, L., Zhao, S., Zhang, X., Li, L., Huang, J., et al. (2015). Grey Wolf Optimizer for parameter estimation in surface waves. *Soil Dyn. Earthq. Eng.* 75, 147–157. doi:10.1016/j.soildyn.2015.04.004

Su, H., Li, X., Yang, B., and Wen, Z. (2018). Wavelet support vector machine-based prediction model of dam deformation. *Mech. Syst. Signal Process.* 110, 412–427. doi:10.1016/j.ymssp.2018.03.022

Su, H., Wen, Z., Sun, X., and Yang, M. (2015). Time-varying identification model for dam behavior considering structural reinforcement. *Struct. Saf.* 57, 1–7. doi:10.1016/j.strusafe.2015.07.002

Viswanathan, G. M., Afanasyev, V., Buldyrev, S. V., Murphy, E. J., Prince, P. A., and Stanley, H. E. (1996). Lévy flight search patterns of wandering albatrosses. *Nature* 381 (6581), 413–415. doi:10.1038/381413a0

Wei, B., Yuan, D., Li, H., and Xu, Z. (2019). Combination forecast model for concrete dam displacement considering residual correction. *Struct. Health Monitoring-an Int. J.* 18 (1), 232–244. doi:10.1177/1475921717748608

Xue, Y., Jiang, J., Zhao, B., and Ma, T. (2018). A self-adaptive artificial bee colony algorithm based on global best for global optimization. *Soft Comput.* 22 (9), 2935–2952. doi:10.1007/s00500-017-2547-1

Yang, X., and Deb, S. (2009). "Cuckoo search via lévy flights," in 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC), Coimbatore, India, 09-11 December 2009 (IEEE), 210–214.

Zhang, S., and Zhou, Y. (2015). Grey wolf optimizer based on powell local optimization method for clustering analysis. *Discrete Dyn. Nat. Soc.* 2015, 1–17. doi:10.1155/2015/481360