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Slope stability analysis using black widow optimization hybridized with artificial neural network

Huanlong Hu [1a], Mesut Gör [2b], Hossein Moayedi [3,4c], Abdolreza Osouli [5d] and Loke Kok Foong*[3,4]

[1] *Shenzhen Expressway Engineering Testing Co., Ltd., China*
[2] *Firat University, Engineering Faculty, Civil Engineering Department, Division of Geotechnical Engineering, 23119, Elazığ, Turkey*
[3] *Institute of Research and Development, Duy Tan University, Da Nang 550000, Vietnam*
[4] *Faculty of Civil Engineering, Duy Tan University, Da Nang 550000, Vietnam*
[5] *Civil Engineering Department, Southern Illinois University, Edwardsville, IL, USA*

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Abstract. A novel metaheuristic search method, namely black widow optimization (BWO) is employed to increase the accuracy of slope stability analysis. The BWO is a recently-developed optimizer that supervises the training of an artificial neural network (ANN) for predicting the factor of safety (FOS) of a single-layer cohesive soil slope. The designed slope bears a loaded foundation in different distances from the crest. A sensitivity analysis is conducted based on the number of active individuals in the BWO algorithm, and it was shown that the best performance is acquired for the population size of 40. Evaluation of the results revealed that the capability of the ANN was significantly enhanced by applying the BWO. In this sense, the learning root mean square error fell down by 23.34%. Also, the correlation between the testing data rose from 0.9573 to 0.9737. Therefore, the postposed BWO-ANN can be promisingly used for the early prediction of FOS in real-world projects.

Keywords: black widow optimization; factor of safety; neural network; slope stability analysis

1. Introduction

Slope stability analysis is one of the most important tasks in geotechnical engineering projects (Khorasani *et al.* 2019). Regarding the increasing developments, the landslide has featured as a major environmental catastrophe along with disasters like volcanoes and earthquakes (Lin *et al.* 2018). So far, various finite element-based approaches have promisingly analyzed the factor of safety (FOS) of soil and rock systems (Li *et al.* 2016, Qian *et al.* 2017, Dyson and Tolooiyan 2020). Due to the high robustness of machine learning models in dealing with geotechnical issues, many scholars have employed them for approximating the stability situation of different slopes (Kang *et al.* 2017, Azarafza *et al.* 2020).

Having a more generic discussion, recent advances have been of great facilitating help for engineers and scientists in different fields (Zhang *et al.* 2020b, Zhao and Li 2020, Sun *et al.* 2021) such as energy-related analysis (Zhao *et al.* 2020b, Zuo *et al.* 2020), water treatment (Yang *et al.* 2020; Liu *et al.* 2021), construction and waste reduction (Liu *et al.* 2020a, b, Gao *et al.* 2021), simulations in optic science (Zuo *et al.* 2015; Zuo *et al.* 2017), environmental modeling (Zhang *et al.* 2020a, c, Hong *et al.* 2021), and remote sensing (Han *et al.* 2019). The role of soft computing is crucial as it leads to overcoming the difficulties associated with traditional techniques (Seyedashraf *et al.* 2018, Qiao *et al.* 2021).

In civil engineering domains, soft computing has properly served aiming to handle the computations more conveniently. Simulating mechanical properties of structural components is a popular usage of these models (DeRousseau *et al.* 2018, Alam *et al.* 2020, Chaabene *et al.* 2020, Kim *et al.* 2020, Nguyen *et al.* 2020). Many scholars have worked on concrete parameters (Boğa *et al.* 2013, Zheng *et al.* 2020). Öztaş *et al.* (2006), for instance, successfully applied an artificial neural network (ANN) to simulate the compressive strength. Based on 99.93% accuracy, this study ANN was reported as a capable method. Also, some comparative studies have been conducted to profess the higher capability of intelligent models over regression analysis (Chithra *et al.* 2016).

As for our case of study, Fattahi and Zandy Ilghani (2020) could successfully predict the FOS using a Bayesian Markov Chain Monte Carlo (MCMC) approach. Zhou *et al.* (2019) used a gradient boosting machine model for predicting the slope stability for circular mode failure. Based on the accuracy rate of 0.8654, as well as Cohen's kappa values of 0.7324, the proposed approach could achieve a reliable approximation of the intended parameter. Tien Bui *et al.* (2019) conducted a comparison between various predictive tools of Gaussian process regression, multi-layer perceptron (MLP), multiple linear regression, support vector regression (SVR), and simple linear

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*Corresponding author, Ph.D.,
E-mail: lokekokfoong@duytan.edu.vn
[a] Senior Engineer, E-mail: 609622744@qq.com
[b] Ph.D., E-mail: mgor@firat.edu.tr
[c] Ph.D., E-mail: hosseinmoayedi@duytan.edu.vn
[d] Ph.D., E-mail: aosouli@siue.edu

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regression. Referring to the obtained accuracy scores of 20, 50, 35, 35 and 10, the MLP was superior to other models. Ahour *et al.* (2019) suggested and ANN model for examining the stability of rock slopes based on the generalized Hoek–Brown failure criterion. They concluded that geological strength index, applied surcharge, and rock compressive strength are the most influential parameters. Sari *et al.* (2019) investigated the applicability of adaptive neuro-fuzzy inference system (ANFIS) for simulating the FOS in Guthrie Corridor Expressway, Malaysia.

For more reliable analysis, metaheuristic algorithms have been used for finding the globally optimal solutions in various engineering fields (Chen *et al.* 2016, Wang *et al.* 2017, Xia *et al.* 2017, Moayedi *et al.* 2019a, Xu *et al.* 2019, Yu *et al.* 2021). Inspired by the herding behaviors in nature (e.g., mimicking the behavior of Harris hawks (Chen *et al.* 2020, Zhang *et al.* 2020e) and grey wolf (Zhao *et al.* 2019, Hu *et al.* 2020)), these algorithm apply specific strategies for simulating the problem into their own way, and eventually, finding a global response (Xu and Chen 2014, Zhao *et al.* 2014, 2020a). By some coding modifications, metaheuristic techniques can be employed for model optimizations (Shan *et al.* 2020, Yu *et al.* 2020, Zhang *et al.* 2020d, Tu *et al.* 2021). Apart from engineering issues, medical scientists have used the benefits of these algorithms for purposes like early diagnosis (Hu *et al.* 2015, Shen *et al.* 2016, Li *et al.* 2018, Wang and Chen 2020).

Qi and Tang (2018) used firefly algorithm (FA) for tuning the hyperparameters of in slope stability analysis. They recommended the use of an optimized SVM model for this task, due to the high accuracy obtained for this model. Himanshu *et al.* (2020), Mishra *et al.* (2020), and Bhattacharjya (2020) employed grey wolf optimization (GWO), teaching–learning-based optimization (TLBO), and genetic algorithm (GA) for investigating the critical slip surface in slope stability analysis. Moayedi *et al.* (2019b) proposed a combination of ANN and Harris hawks' optimization (HHO) for optimal prediction of the FOS. The HHO was applied to find the best hyperparameters of the ANN. It was shown that the mentioned strategy results in around 27% improvement in the results. Luo *et al.* (2019) used a hybrid of cubist algorithm and particle swarm optimization for slope stability modeling in an open-pit mine. The proposed model (with around 98.1% accuracy) surpassed benchmark models including the SVM. Wang *et al.* (2020) applied the hybrid of MLP and GA optimization for predicting the FOS of a purely cohesive slope. The calculated error values of 0.097 and 0.107 revealed the efficiency of the GA in fine-tuning of the ANN. Hoang and Pham (2016) synthesized the FA and least squares support vector classification for slope stability analysis. According to the experimental results, around 4% enhancement was resulted by the proposed hybrid model.

Based on the high efficiency of metaheuristic algorithms in the field of slope stability modeling (Mishra *et al.* 2019, Singh *et al.* 2019, Yuan and Moayedi 2019), this research is conducted to examine the optimization efficiency of a novel search scheme, namely black widow optimization (BWO). The BWO is developed by Hayyolalam and Kazem (2020) and has not been used in earlier studies. It is here applied for fine-tuning the ANN parameters in predicting the FOS of a cohesive soil slope. The performance of the hybrid model is compared to the typically-trained ANN for evaluating the efficacy of the BWO technique in relating the FOS to its influential factors.

2. Methodology and established database

A total of 630 (rows of) data are used in this study. These data are recorded from a vast finite element modeling in the Optum G2 environment (Krabbenhoft *et al.* 2015). In his sense, a footing (with dimension D) along with a single-layer slope is considered as the basic system. Notably, the material was a cohesive soil that only had undrained cohesive strength (C_u). Seven different values of 25, 50, 75, 100, 200, 300 and 400 *kPa* are set for the *Cu*. Another variable of the soil slope is its angle (β) that takes the values 5, 30, 45, 60, and 75°. The mechanical parameters assigned to the proposed system are presented in Table 1.

The surcharge applied through the footing (w) is another influential factor that varies for 50, 100, and 150 KN/m^2. Moreover, each stage is tested for six different setback ratios (d/D) of 0, 1, 2, 3, 4, and 5. The factor of safety

Table 1 Descriptive statistics of the compressive strength and key factors

Parameter	Value/Name						
Material type	Mohr-Coulomb						
Poisson ratio	0.35						
Internal friction angle (°)	0						
Soil unit weight (kN/m^3)	18						
Modulus of Young (kPa)	1000	2000	3500	5000	9000	15000	30000
	For the C_u =						
	25 kPa	50 kPa	75 kPa	100 kPa	200 kPa	300 kPa	400 kPa

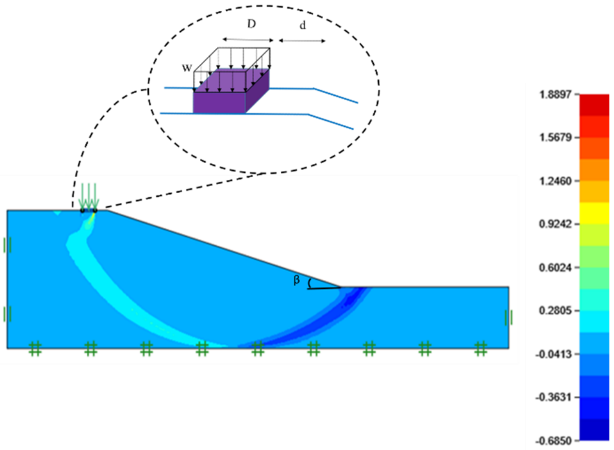
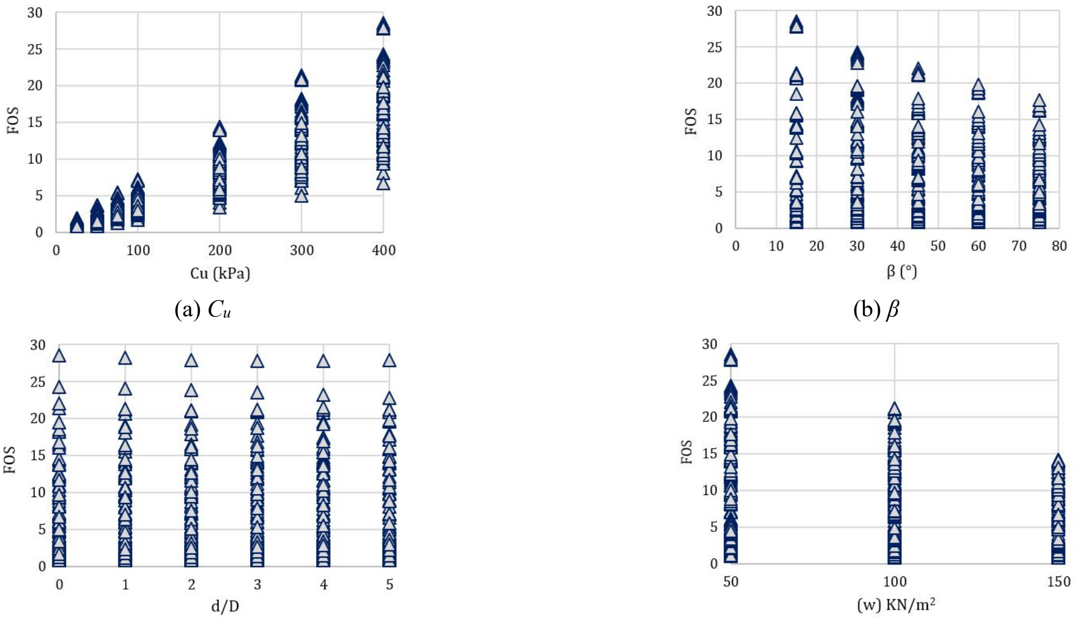


Fig. 1 A schematic view of the designed system for computing the FOS



(a) C_u (b) β

(c) d/D_s (d) w

Fig. 2 The distribution of the FOS versus the parameters of the footing and soil slope

(FOS) is obtained and recorded for each analysis. The FOS is a common indicator of geotechnical stability and slope deformations and is considered as the dependent (i.e., target) variable in this study. Fig. 1 shows (the horizontal strain of) an analyzed slope where C_u = 75 kPa, d/D = 1, w = 100 KN/m^2, and β = 15°.

Moreover, the distribution of the FOS versus each influential factor is depicted in Fig. 2. Among the 360 tested stages, 504 instances are randomly selected as training data for analyzing the FOS based on the C_u, β, d/D, and w. Then, the remaining 126 instances are tested to evaluate the ability of the models for predicting the FOS in stranger conditions.

2.1 Methodology

Artificial neural network: The ANNs, as was explained, are one of the most powerful processors applied to various engineering problems. The main principle of the ANN is mimicked by the neural relationship in the biological systems. The basic model was first developed by McCulloch and Pitts (1943). Different notions of ANN (e.g., multi-layer perceptron (MLP) (Hornik 1991), radial basis function (Orr 1996), and general regression (Specht 1991)) have been successfully used for predicting engineering parameters. Fig. 3 shows the structure of an MLP. This network is frequently trained by the back-propagation algorithm that works based on the error correction strategy (Hecht-Nielsen 1992). Also, the Levenberg-Marquardt (LM) algorithm is used as the conventional learning algorithm of the MLP (Moré 1978). The output of the lth processor lying in the layer n is calculated as follows

$$y_l^n\,(t) = f\left[\sum\nolimits_{j=1}^{P} w_{lj}^n\,(t)\; y_j^{n-1}\,(t) + \lambda_l^n\right] \qquad (1)$$

in which, f is the activation function, w_{lj}^n stands for the weight and λ_l^n symbolizes the bias.

The difference between the overall product of the MLP with the expected target is measured as the error and based on the back-propagation theory, it is reduced through adjusting the weights and biases during the implementation.

Black widow optimization: The BWO is inspired by the lifestyle of a so-called species of spiders (Fig. 4). Spider pairs aim to reproduce offspring as a new generation. During this process, the female black widow eats her mate and releases the carried sperms into her egg sacs. After 11 days, spiderlings come out of these sacs. They live on the maternal web for a while (around one week) during which, sibling cannibalism is witnessed. The wind then carries them away (Perampaladas *et al*. 2008, Berning *et al*. 2012).

This technique is proposed by Hayyolalam and Kazem (2020) in 2020 for dealing with engineering problems. It is a population-based method that starts with generating

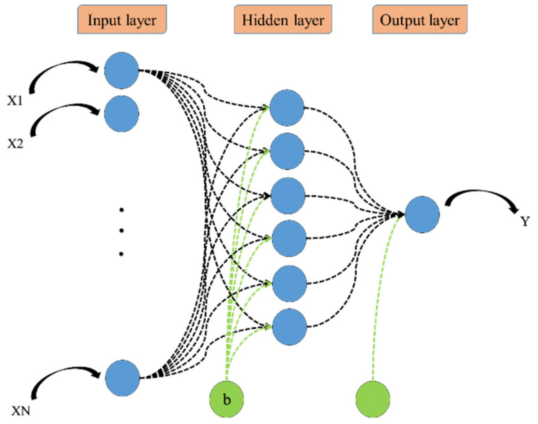


Fig. 3 The MLP network architecture

Fig. 4 Female black widow

a random population of spiders where each one represents a candidate solution. In the BWO, the structure of the solution is called widow. In an N-dimensional problem, a widow is defined as follows

$$Widow = [x_1, x_2, \dots, x_N] \tag{2}$$

The fitness of the widow is also obtained by applying a fitness function as

$$Fitness = f(widow) = f(x_1, x_2, \dots, x_N) \tag{3}$$

In the first step of the algorithm, a $N_{pop} \times N$ widow matrix is created. Next, the pairs are randomly selected to do the mating process. This process is carried out in a separate web for each pair. An alpha (α) array of random numbers is generated to produce the offspring as follows

$$\begin{cases} y_1 = \alpha \times x_1 + (1-\alpha) \times x_2 \\ y_2 = \alpha \times x_2 + (1-\alpha) \times x_1 \end{cases} \tag{4}$$

where x_1 and x_2 stand for the parents and y_1 and y_2 denote the offspring. This process is repeated for $N/2$ iterations and duplicated random numbers cannot be used. The female black widow and her children are then added to an array sorted based on their fitness. The elite members are finally added to the new population.

There are three types of cannibalism in the BWO. First, the husband is eaten by the female during sexual cannibalism. Notably, the fitness value of each member determines its gender. Sibling cannibalism is another type in which more powerful spiderlings eat the weaker members. The number of survivors is here determined by a cannibalism rating (CR). The third kind occurs once the baby spider eats the mother.

The mutation is another significant step of the BWO in which Mutepop numbers of the agents are randomly selected. As Fig. 5 shows, two elements are randomly exchanged in each selected solution.

The pseudo-code of the BWO algorithm is presented as follows (Hayyolalam and Kazem 2020)

The pseudo-code of the BWO algorithm

```
// Initialization phase:
The initial individuals are generated
For an N-dimensional problem, each T represents an (N-dimensional) array of chromosomes.

// Running the loop until a stopping criterion is met:
 1- Calculate the number of reproductions (NR) with respect to the procreation rate;
 2- Select the best NR solution and save them in T1;

// Procreation and cannibalism
 3- For $i$ = 1 to NR
      a) Select the parents from T1 based on a random selection;
      b) Produce N children using Eq. (4);
      c) Eliminate the husband;
      d) Eliminate some of the children with respect to the cannibalism rate;
      e) Save the rest of the solutions in T2;
End for

// Mutation phase:
 4- Calculate the number of mutation children (NM) with respect to the mutation rate;
 5- For $i$ = 1 to NM
      a) Select a candidate solution from T1;
      b) Generate a new solution through mutating a chromosome of the proposed solution
      c) Save the new solution in T3;
End for

// Updating:
 6- Update as T = T2 + T3;
 7- Return the best-fitted solution
Return the best-fitted solution from T;
```

Further studies for the BWO algorithm can be found in the literature like (Houssein *et al.* 2020, Premkumar *et al.* 2020).

Hybridization: As explained, this study investigates the optimization efficiency of the BWO metaheuristic algorithm for proper adjustment of ANN parameters in stability analysis of a cohesive soil slope. In order to optimize the weights and biases of the ANN, training of this model should be supervised by the BWO. First, the best number of hidden neurons needs to be determined by a trial

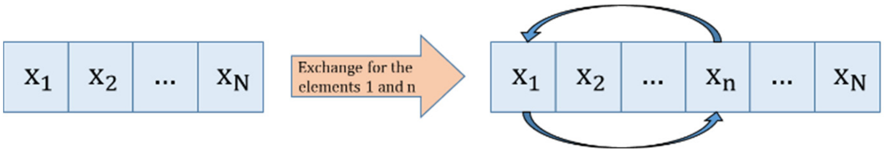


Fig. 5 The mutation step of the BWO algorithms

and error process. The MLP network was tested by ten different numbers of hidden units (i.e., 1, 2, …, 10); and it was shown that six neurons construct the best-fitted structure.

The general equation of a 4 × 6 × 1 MLP was given to the BWO as the problem function. The weights and biases were the variables of the problem. The BWO-ANN hybrid was created and tested for ten different population sizes of 5, 10, 15, 20, 25, 30, 35, 40, 45, and 50. This process was conducted to ensure the most suitable complexity will be used. A total of 1000 repetitions was considered to minimize the objective function of the problem. In this work, root mean square error (RMSE) was used to reflect the objective function at each repetition. Let $O_{i\ predicted}$ and $O_{i\ observed}$ be the modeled and expected FOSs, then this index is defined as follows:

$$RMSE = \sqrt{\frac{1}{K}\sum_{i=1}^{K}\left[\left(O_{i_{observed}} - O_{i_{predicted}}\right)\right]^{2}} \tag{5}$$

where K is the number of instances.

The obtained RMSE values and the convergence curves of the tested BWO-ANN models are shown in Figs. 6 and 7, respectively. As is see, the BWO-ANN with the population size of 40 yields the lowest RMSEs in both training and testing phases (1.011303714 and 0.981778099, respectively). From the convergence curves, it can be demonstrated that the first 20 iterations reduce the majority of the error.

Fig. 6 Obtained values of the objective function

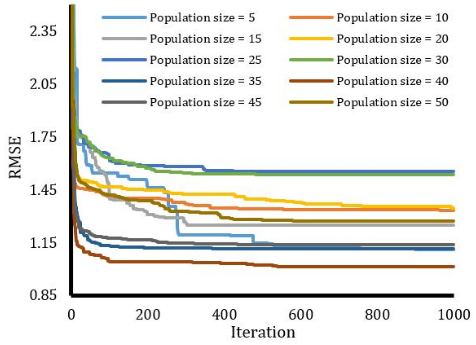


Fig. 7 The convergence curves of the tested models

2.2 Quality assessment indices

As was explained, the RMSE was used as an error criterion for monitoring the optimization behavior of the BWO-ANN ensemble. As well as the RMSE, mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2) are also used as the second, third, and fourth accuracy criterion. Assuming $\bar{O}_{observed}$ as the average value of the expected FOSs, the MAE and R^2 are formulated as follows

$$MAE = \frac{1}{K}\sum_{i=1}^{K}\left|O_{i_{observed}} - O_{i_{predicted}}\right| \tag{6}$$

$$MAPE = \frac{1}{K}\sum_{i=1}^{K}\left|\frac{O_{i_{observed}} - O_{i_{predicted}}}{O_{i_{observed}}}\right| \times 100 \tag{7}$$

$$R^{2} = 1 - \frac{\sum_{i=1}^{K}\left(O_{i_{predicted}} - O_{i_{observed}}\right)^{2}}{\sum_{i=1}^{K}\left(O_{i_{observed}} - \bar{O}_{observed}\right)^{2}} \tag{8}$$

3. Results and discussion

3.1 Quality assessment and comparison

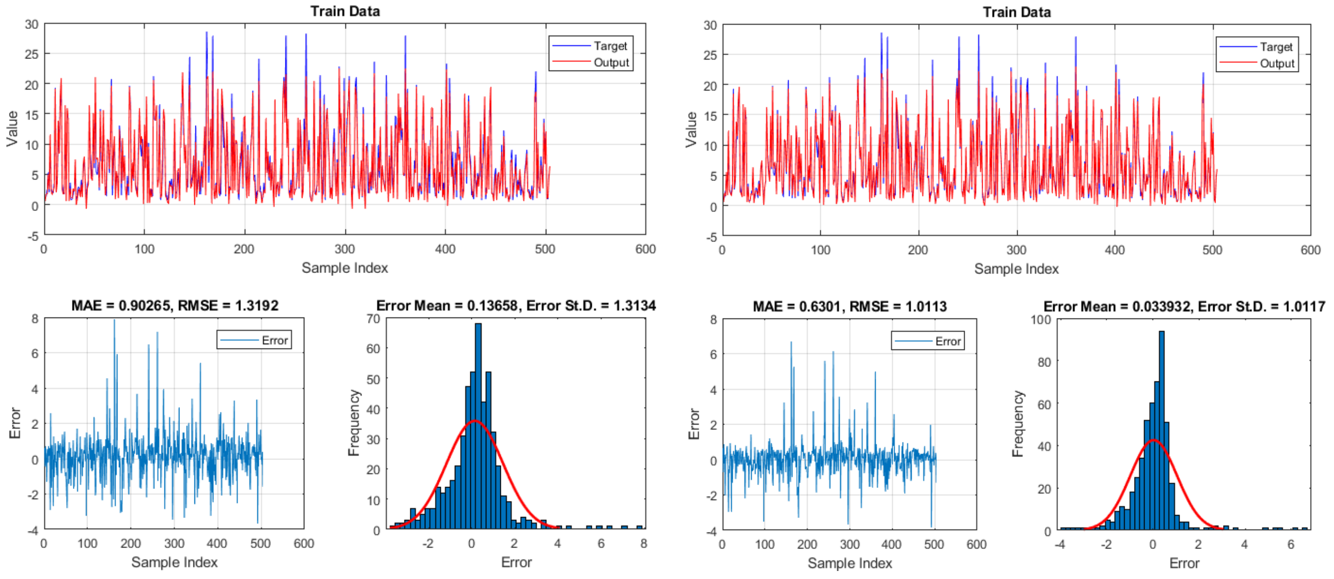
To examine the effectiveness of the BWO algorithm, the results of the corresponding ANN must be compared to those produced by the typically trained ANN (i.e., LM-ANN). Utilizing the mentioned accuracy criteria, this is done for both training and testing data to evaluate the changes in the learning and prediction capability of the ANN.

Fig. 8 shows the training results. The patterns of the modeled and expected FOS are compared. In this figure, depicted error represents the direct difference between the modeled and expected FOS for each instance. The histogram diagrams are also shown to compare the frequency of the error values. These figures demonstrate that the FOS pattern detected by the BWO-ANN is more compatible with the target pattern. The minimum and maximum values of the ANN error in the training phase are -3.6394 and 7.8709, while these values are -3.8295 and 6.6520 for the BWO-ANN.

The reduction of the RMSE from 1.3192 to 1.0113 indicates that the BWO has performed more efficiently than the LM in training the ANN. The MAE also experienced a fall from 0.9026 to 0.6301.

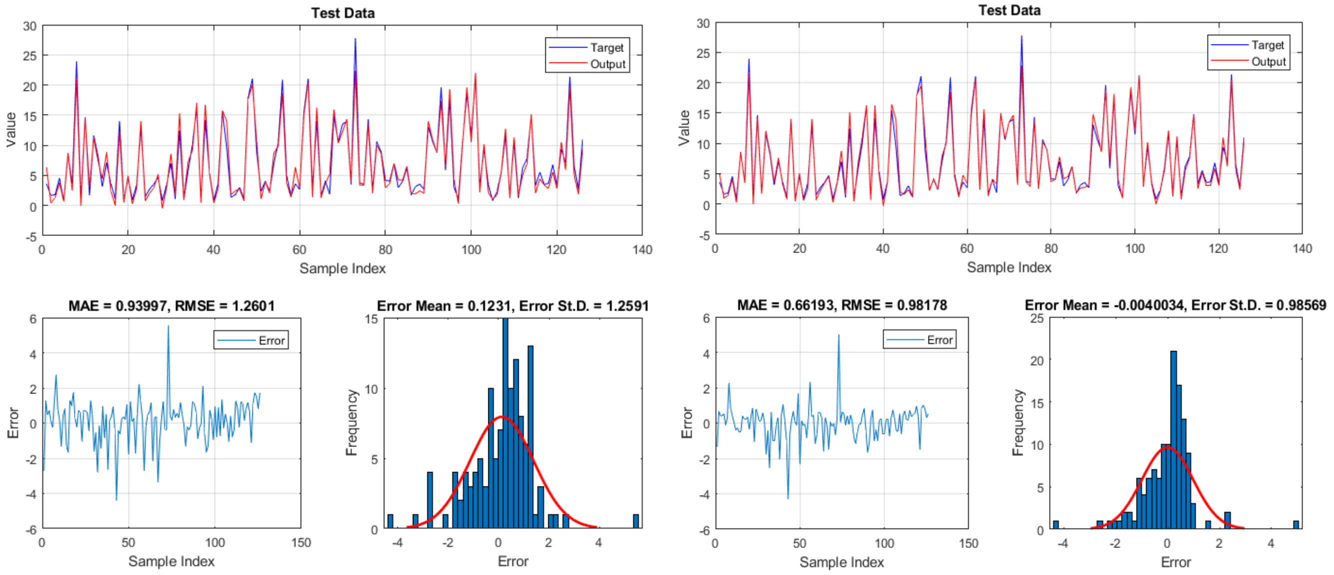
The testing products are also compared to the target values to evaluate the prediction robustness of the BWO algorithm. The errors, in this phase, range in [-4.3953, 5.5204] for the ANN. This extent is shrunk to [-4.3186, 5.0025] after replacing the LM with BWO. The RMSE and MAE of the ANN were 1.2601 and 0.9399, respectively, which fell down to 0.9817 and 0.6619 as the results of applying the BWO algorithm.

The correlation of the results is also presented to evaluate the consistency of the models' products. The results are shown in Fig. 10. In this work, the correlation is indicated by the R^2 index which as is known, its ideal value



(a) LM-ANN (b) BWO-ANN

Fig. 8 The training results



(a) LM-ANN (b) BWO-ANN

Fig. 9 The testing results

is 1.00. The R^2s obtained for the training and testing phase of the ANN were 0.9539 and 0.9573, respectively. The increase of these values to 0.9728 and 0.9737 for the BWO-ANN denotes that the weighs and biases proposed by the metaheuristic algorithm create a more generalizable FOS pattern. This claim can be supported by lower MAPEs of the BWO-ANN (16.03 and 16.53% for the training and testing results, respectively), in comparison with the unreinforced ANN (23.17 and 23.29%).

Since the accuracy plays a very crucial role in simulations, especially in civil engineering works, enhancing the performance of the models is of great importance. Although ANNs can nicely deal with many simulations which consists of abrupt changes in the behavior of the proposed parameter (Seyedashraf *et al.* 2018), they may encounter issues like local minima (Nguyen *et al*. 2019).

The accuracy improvement achieved with the help of the BWO algorithm in this work can results in a more reliable evaluation of the stability of soil slopes. For instance, considering a marginal value that distinguishes between the failure and stability of a slope (Yuan and Moayedi 2019), the low accuracy of a model can lead to an unreliable prediction. Computational issues are more highlighted when model is likely to be misled by confusing intricate data. For example, having a look at Figure 2 – (c), it can be realized that a wide range of FOS is obtained for various d/D ratios. Therefore, utilizing this metaheuristic optimizer is recommended along with typical ANN. In a study by Moayedi *et al*. (2019b), the prediction accuracy of a conventional ANN was enhanced by an HHO algorithm. In this sense, the RMSE of prediction was reduced from 2.08 to 1.65. At a glance, the amount of the decreased error may not seem so significant, but as discussed, it is worth it in sensitive engineering works like slope stability.

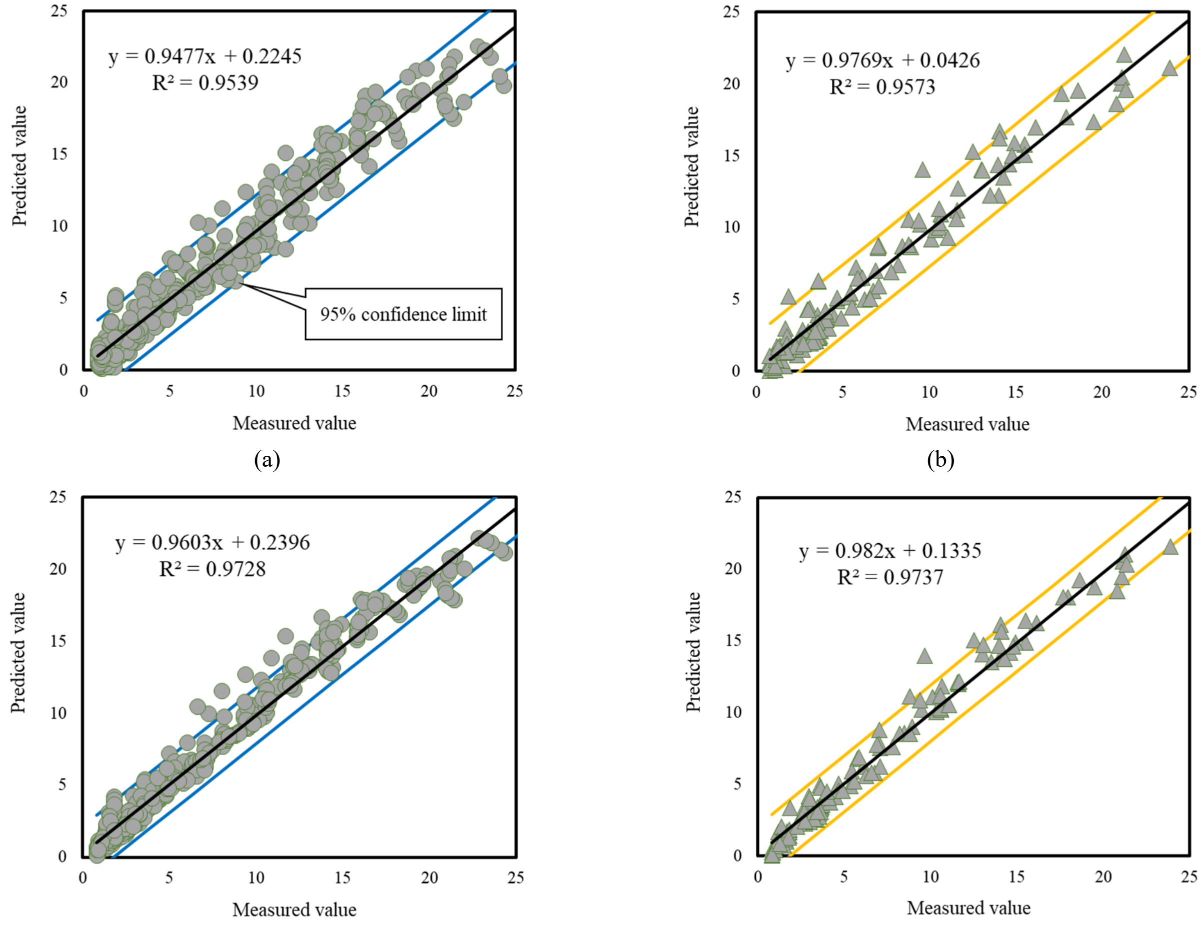
However, the efficiency of a model consists of more parameters, for example, the complexity of calculation, as well as the time of optimization. Hence, some ideas might form future works toward increasing the efficiency of the models. Testing different optimization technique (like electromagnetic field optimization (Moayedi *et al*. 2021)) may introduce fast techniques. Network structure and the size of dataset are other important parameters that can affect the complexity of the model. As will be seen in the next section, reducing the number of computational units of the ANN can significantly decrease the computational parameters, and consequently, the complexity.

Another appreciable point regarding the used data is about validation of the results. Although the models showed great promise in dealing with data finite element-based simulation, real-world verifications (i.e., applying the model to the real slopes) can reflect a more comprehensive validation. So, it is an interesting motivation for next projects.

- Presenting the neural predictive formula

The above results showed that the BWO-ANN is superior to the typical ANN in both analyzing and generalizing the FOS pattern. It indicates that the BWO metaheuristic scheme can acquire a more reliable relationship between the considered key factors (i.e., C_u, β, d/D, and w) with the stability of the slope system. Hence, in this section, the weights and biases that are optimized by the BWO are presented in Eq. (9) as an FOS predictive formula. Recalling Fig. 3, this equation is extracted from the only output neuron of the network. The weights are multiplied by 6 middle parameters of α, β, γ, δ, ε, and ζ and the resulted value is added to a bias value to give the FOS. Similarly in the hidden layer, the weights and biases of each hidden neuron are applied to the inputs under a so-called activation function “Tansig”, This function is presented in Eq. (13).

$$\begin{aligned} FOS_{BWO-ANN} = {} & -0.2185 \times \alpha - 0.5950 \times \beta \\ & -0.9463 \times \gamma - 0.2814 \times \delta \\ & +0.5360 \times \varepsilon + 0.5653 \times \zeta \\ & +0.2465 \end{aligned} \tag{9}$$



(a) (b) (c) (d)

Fig. 10 The correlation of the training and testing results for the (a) and (b) LM-ANN; and (c) and (d) BWO-ANN models

$$\begin{bmatrix} \alpha \\ \beta \\ \gamma \\ \delta \\ \varepsilon \\ \zeta \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} 0.8193 & -1.3747 & 0.9852 & 1.1266 \\ 1.4220 & 1.2298 & -1.1144 & -0.1567 \\ 1.4582 & -1.0395 & 0.4521 & -1.1788 \\ -1.0922 & 0.8464 & 0.2701 & -1.6789 \\ 0.4910 & -0.6328 & 1.8111 & -0.9378 \\ -1.7121 & 0.4511 & -0.4968 & 1.1914 \end{bmatrix} \begin{bmatrix} Cu \\ \beta \\ \frac{d}{D} \\ w \end{bmatrix}\right) + \begin{bmatrix} -2.1911 \\ -1.3147 \\ -0.4382 \\ -0.4382 \\ 1.3147 \\ -2.1911 \end{bmatrix}\right) \tag{10}$$

$$Tansig(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{11}$$

4. Conclusions

Proper analysis of slope stability is a prerequisite in many civil engineering projects. The evaluation is mostly carried out by obtaining a factor of safety. In this study, a novel metaheuristic technique, namely black widow optimization combined with neural computing was applied to a single-layer soil slope to predict the FOS. The proposed BWO-ANN was optimized in terms of population size. As a result, investigating the effect of this parameter is valuable to find the optimal configuration because the algorithm does not follow a certain behavior with increasing/decreasing the population size. Both LM-ANN and BWO-ANN gained a reliable understanding of the FOS pattern. However, the learning error of the ANN experienced a fall from 1.3192 to 1.0113 when the LM was replaced with BWO. The prediction capability of the ANN was also enhanced, due to the correlation index that rose from 0.9573 to 0.9737. All in all, the findings revealed a complicated network like ANN can function more accurately when it is assisted by a proper optimization method. Thus, the computational shortcomings of the conventional version (e.g., local minima) can be remedied in this way. Hence, future projects are recommended to focus on evaluating most potential optimization techniques in a comparative way so as to determine the best predictive model.

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