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Analyzing the bearing capacity of shallow foundations on two-layered soil using two novel cosmology-based optimization techniques

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Abstract. Due to the importance of accurate analysis of bearing capacity in civil engineering projects, this paper studies the efficiency of two novel metaheuristic-based models for this objective. To this end, black hole algorithm (BHA) and multi-verse optimizer (MVO) are synthesized with an artificial neural network (ANN) to build the proposed hybrid models. Based on the settlement of a two-layered soil (and a shallow footing) system, the stability values (SV) of 0 and 1 (indicating the stability and failure, respectively) are set as the targets. Each model predicted the SV for 901 stages. The results indicated that the BHA and MVO can increase the accuracy (i.e., the area under the receiving operating characteristic curve) of the ANN from 94.0% to 96.3 and 97.2% in analyzing the SV pattern. Moreover, the prediction accuracy rose from 93.1% to 94.4 and 95.0%. Also, a comparison between the ANN's error decreased by the BHA and MVO (7.92% vs. 18.08% in the training phase and 6.28% vs. 13.62% in the testing phase) showed that the MVO is a more efficient optimizer. Hence, the suggested MVO-ANN can be used as a reliable approach for the practical estimation of bearing capacity.

Keywords: artificial neural network; bearing capacity; black hole algorithm; multi-verse optimizer; stability analysis

1. Introduction

Ultimate bearing capacity reflects the limited settlement of foundation and proper determination of this factor is of high importance in construction projects (Shahnazari and Tutunchian 2012). Many scholars have tried to present evaluative formulas for computing this term (e.g., Terzaghi (1943), Hansen (1970), Meyerhof (1963)). The concepts of the mentioned efforts are mainly based on the parameters like the shearing resistance angle and the footing geometry. Laboratory works (Azan and Haddad 2019, Sultana and Dey 2019), as well as experimental and analytical approaches [7; 8], have also resulted in promising solutions for bearing capacity assessment. But regarding some noticeable drawbacks of these methods like being time-consuming and costly, the use of machine learning methods has been highly recommended by scientists (Moayedi *et al.* 2020, 2021).

Earlier, numerous sophisticated methods (e.g., numerical and simulative tools applied to early monitoring and sensors (Sun *et al.* 2018), fluid transfer (Xu *et al.* 2021), urban planning (Lu *et al.* 2021), infill walls (Onat and Gul 2018), structural engineering and concrete-related analysis (Malekzadeh and Vosoughi 2009, Chen *et al.* 2010, Vosoughi 2016, Luo *et al.* 2021), etc.) were of great assistance to engineers in various fields (Feng *et al.* 2021, Li *et al.* 2021). The advent of machine learning, however, made huge facilitations to these analyses through efficient soft computing. Simulating the power of generators, for instance, is a well-known application of machine learning models (Kurt and Gör 2014, Çelik *et al.* 2017, Çelik and Gör 2019). More particularly for civil engineering works, these models have successfully predicted different phenomena like dam break (Seyedashraf *et al.* 2018), small scale parameter of FG nanobeams (Vosoughi and Darabi 2016), landslide susceptibility (Moayedi *et al.* 2019b), pile capacity (Liang *et al.* 2020), multilayered half-spaces (Vosoughi *et al.* 2014), Pasternak elastic foundation parameters (Khalili and Vosoughi 2018), etc.

Sadrossadat *et al.* (2018) employed gene expression programming and adaptive neuro-fuzzy inference system (ANFIS) for estimating the ultimate bearing capacity of rock foundations. They showed that these models outperform earlier traditional approaches. Another study for proving the efficiency of genetic programming was conducted by Tsai *et al.* (2013). Likewise, the potential of k-nearest neighbor was investigated by Jabbar *et al.* (2018). Regarding the error values of 1.54 and 2.03, as well as the correlations of 97 and 93%, the proposed model performed more accurately than a multiple linear regression tool. Pohjankukka *et al.* (2016) explored the efficiency of various linear and non-linear machine learning models for predicting the bearing capacity of boreal forest soil for the suitability of machinery operation. Das and Dey (2018) could successfully predict the bearing capacity of stone columns installed in soft clay by employing an artificial neural network (ANN). Ornek (2014) showed the robustness of ANN for analyzing the ultimate loads of eccentric-inclined loaded footings settled on sandy beds. More studies about the application of intelligent models in similar subjects can be found in Refs. (Soleimanbeigi and

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Hataf 2005, Padmini *et al*. 2008, Kuo *et al*. 2009).

The ANNs can process non-linear calculations with high reliability. Multi-layer perceptron (MLP) (Hornik *et al.* 1989, Hornik 1991) is one of the most powerful notions of these tools which benefits the backpropagation (BP) (Hecht-Nielsen 1992) method along with Levenberg-Marquardt (LM) algorithm (Moré 1978) for learning. Despite high prediction capability, meet with some computational deficiencies. Most importantly, getting trapped in local minima prevents them to find the best-fitted solution (Burse *et al*. 2011, Moayedi *et al*. 2018).

As a promising solution to such problems, various search algorithms have been suggested by engineers (Vosoughi and Darabi 2017, Vosoughi *et al*. 2018). Moayedi *et al*. (2019a) examined the efficiency of four metaheuristic schemes of ant colony optimization (ACO), league champion optimization (LCA), whale optimization algorithm (WOA), and moth–flame optimization (MFO) for optimal adjustment of neural computing parameters in bearing capacity perdition. Apart from proving the adequacy of all four algorithms in optimizing the ANN (i.e., reducing the prediction error by around 34, 13, 14, and 18%, respectively), the ACO (with 94.4% accuracy) was introduced as the most efficient optimizer. Likewise, Kalinli *et al*. (2011) used a parallel ACO algorithm for proposing an improved Meyerhof formula in the bearing capacity modeling of shallow foundations installed on granular soil. The applicability of two optimizers that work based on the foraging behavior of ant lion and spotted hyena was examined by Liu *et al*. (2019).

Moreover, other types of metaheuristic algorithms (e.g., biogeography-based optimization (Liu *et al*. 2019), Harris hawks optimization and dragonfly algorithm (Moayedi *et al*. 2021), particle swarm optimization (Harandizadeh *et al.* 2019)) have been effectively used for optimizing the problem of bearing capacity in different conditions. But the wide variety of these techniques, as well as the emerging of new capable ones, encouraged the authors to examine the efficiency of two novel optimizers, namely black hole algorithm (BHA) and multi-verse optimizer (MVO) for fine-tuning the ANN in failure/stability approximation of a two-layered soil system. This point is fulfilled by comparing the results of the hybrid models with the typically-trained ANN. Before this, some literature have reported successful usages of these two algorithms for training machine learning models like ANFIS and support vector machine (Faris *et al*. 2018, Munoz *et al*. 2018, Al-qaness *et al*. 2019), and more particularly for neural network in various fields (e.g., BHA (Salih 2019, Pashaei and Pashaei 2021) and MVO (Faris *et al*. 2016, Jamali 2021)). However, according to the best knowledge of the author, no previous study has used the BHA and MVO incorporated with ANN for the problem of bearing capacity.

2. Materials and methods

In this research, a finite element dataset is used for training and validating the performance of the intelligent models. In detail, a shallow footing was designed on a two-layered soil with Mohr-Coulomb material model. The system was analyzed by 15-node triangular elements. The information of seven key factors of the mentioned system, namely unit weight (UW) ($\frac{kN}{m^3}$), friction angle (FA), elastic modulus (EM) ($\frac{kN}{m^2}$), dilation angle (DA), Poisson's ratio (PR) (v), applied stress (AS) ($\frac{kN}{m}$), and setback distance (SD) (m) are collected to be the input variables. The settlement (m) values of 901 implemented stages are then obtained as the target. Fig. 1 illustrates this process.

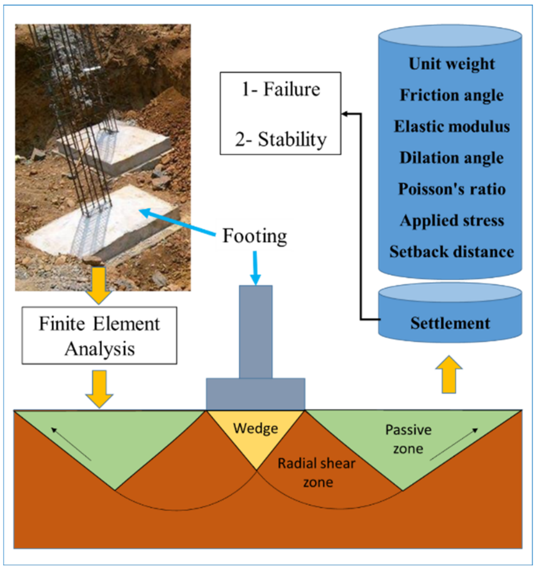


Fig. 1 Schematic view of the data provision process

The resulted target values range from 0 to 10 cm. Settlements lower than 5 cm indicate the stability of the system, and vice versa, the failure of the system is represented by the settlement values higher than 5 cm. In this sense, stability and failure are denoted by 0 and 1 values.

Fig. 2 shows the histogram of the data. Moreover, Table 1 presents the descriptive statistics for each variable.

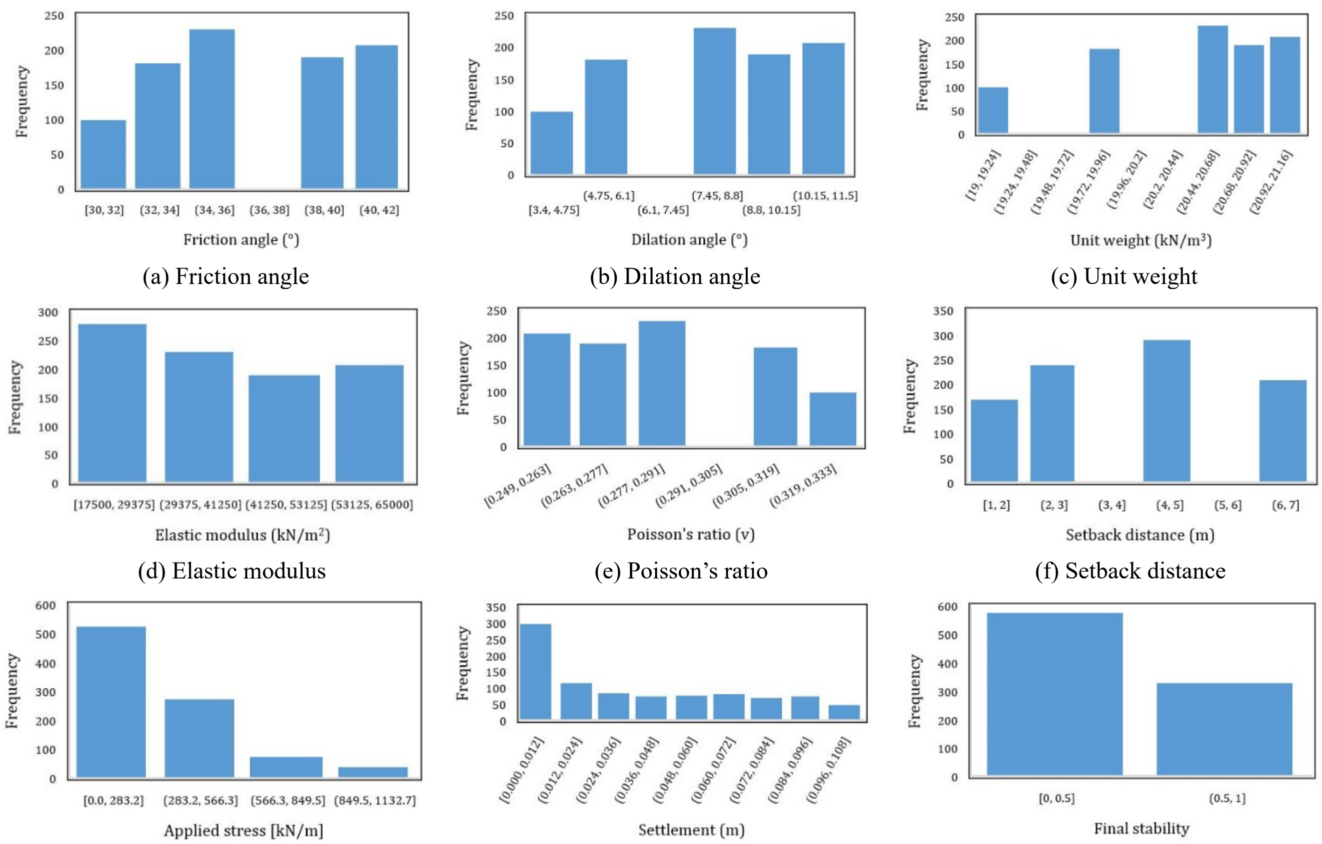
Regarding the division proportion of 80:20, **721** samples are randomly selected as training data. These data are given to the intelligent models, in order to infer the relationship between the stability value (SV) and conditioning factors. After deriving the SV pattern, the models are applied to the remaining 180 samples to evaluate their performance for stranger conditions.

A feature validity is applied to analyze the contribution of each input factor to the settlement of the system. In this way, a permutation-based importance analysis is carried out through a random forest model (Breiman 1996) in the MATLAB environment. Fig. 3 shows the results, according to which, the AS has the greatest effect.

2.1 Methodology

2.1.1 Black hole algorithm

Proposed by Hatamlou (2013), the name BHA represents a newly-developed metaheuristic algorithm for optimization tasks. The algorithm is based on the formation process of a black hole in cosmology. Like other optimization algorithms, the BHA needs to scatter a random



(a) Friction angle (b) Dilation angle (c) Unit weight

(d) Elastic modulus (e) Poisson's ratio (f) Setback distance

(g) Applied stress (h) (i) Final stability

Fig. 2 The histogram of the dataset parameters

Table 1 Descriptive statistics of the compressive strength and key factors

	Minimum	Maximum	Mean	Standard deviation
Friction angle	30.0000	42.0000	36.7458	3.9094
Dilation angle	3.4000	11.5000	8.2777	2.6143
Unit weight (kN/m^3)	19.0000	21.1000	20.4376	0.6549
Elastic modulus (kN/m^2)	17500.0000	65000.0000	41087.6804	16408.7231
Poisson's ratio (v)	0.2490	0.3330	0.2860	0.0276
Setback distance	1.0000	7.0000	4.1898	2.0754
Applied stress (kN/m)	0.0000	1132.6538	289.7388	236.9661
Settlement (m)	0.0000	0.1000	0.0380	0.0325

population (over the search space) at the first stage. The operators aim to evolve individuals to achieve the best possible solution. This process comprises moving the stars toward the black hole. The stars inside the horizon barrier are then replaced with these new individuals.

$$x_i\,(t+1) = x_i\,(t) + rand(0,1) \times \left(x_{BH} - x_i(t)\right) \quad i = 1,2,\ldots,m \tag{1}$$

in which, the old and new position (in iteration t and t + 1) of the star i symbolized by $x_i\,(t)$ and $x_i\,(t+1)$, respectively. x_{BH} denotes the black hole position and *rand* (*0*, *1*) gives a random value from 0 to 1.

Once the star has a more promising solution than the black hole, its position is exchanged. For doing this, the star may cross with the event horizon. If one star is disappeared, a new individual is born in a random position. Assuming f_{BH} and f_i respectively as the fitness value of the black hole and the proposed star, Eq. (2) gives the radius of Schwarzschild

$$R_S = \frac{f_{BH}}{\sum_{i=1}^{M} f_i} \tag{2}$$

where *M* stands for the total number of stars (Heidari and Abbaspour 2014). More details regarding the mechanism of the BHA can be found in earlier studies (Deeb *et al*. 2020, Wang *et al*. 2021, Khare *et al*. 2022).

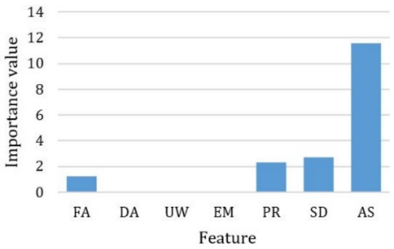


Fig. 3 Importance assessment of the dataset

2.1.2 Multi-verse optimizer

The MVO was suggested by Mirjalili *et al.* (2016) in 2016. It is inspired by a rule in the multi-verse theories. More clearly, it mimics the interactions between multiple universes with cosmological masses including wormholes, black holes, and white holes. This process develops a population-based global optimizer. Two parameters of the MVO are wormhole existence probability (WEP) and traveling distance rate (TDR) which determine the period and the amount of change in the solutions. The WEP and TDR are formulated as follows

$$WEP = a + t \times \left(\frac{b-a}{T}\right) \tag{3}$$

$$TDR = 1 - \frac{t^{1/q}}{T^{1/q}} \tag{4}$$

where t represents the current iteration and the minimum and maximum are shown by a and b, respectively. Also, T stands for the maximum number of iterations and q denotes the exploitation accuracy. Notably, q is an important parameter of the TDR and is proportional to the exploitation emphasized.

The position of the found solutions is adjusted based on the following relationships

$$x_i^j = \begin{cases} \begin{cases} x_j + TDR + \left((ub_j - lb_j) \times e_4 + lb_j\right) & if\ e_3 < 0.5 \\ x_j - TDR + \left((ub_j - lb_j) \times e_4 + lb_j\right) & if\ e_3 \geq 0.5 \end{cases} & if\ e_2 < WEP \\ x^j_{Roulette\,Wheel} \quad if\ e_2 \geq WEP \end{cases} \tag{5}$$

where x_i^j is the j^th parameter in i^th member, x_j indicates the j^th element of the swarm and its upper and lower bound is shown by ub_j and lb_j, respectively. The terms e_2, e_3, and e_4 represent random values generated between 0 and 1. Also, $x^j_{Roulette\,Wheel}$ is the solution element chosen by the roulette wheel selection strategy.

According to these equations, the best position obtained so far (using the WEP) is the basis of updating the positions. So, in the MVO, the solution is enhanced by increasing the WEP (Faris *et al.* 2018). For further mathematical details of the MVO, previous studies like (Hans and Kaur 2020, Sundaram 2020, Gharehpasha *et al.* 2021) are recommended.

3. Results and discussion

In this research, the BHA and MVO metaheuristic algorithms are synthesized with an artificial neural network for bearing capacity analysis. The basic model is a typical ANN trained by the LM learning technique. The results are presented and discussed in this section to evaluate the efficiency of the BHA and MVO.

First, a sensitivity analysis was carried out to discover the best-fitted number of hidden units of the ANN. Considering the number of input and target variables, the ANN takes the form of 7 × NHU × 1 where NHU is the number of hidden units. Ten different values (1, 2, …, and 10) were tested for this parameter and it was shown that 6 constructs the best network.

3.1 Creating and optimizing the BHA and MVO-based ensembles

Having the structure of the selected ANN network (i.e., 7 × 6 × 1), it comprises 42 weights in the first void, i.e., between the input and hidden layer, 6 weights in the second weights, i.e., between the hidden and output neurons, 6 bias terms belonging to hidden neurons, and 1 bias term belonging to the output neuron. All in all, a total of 55 parameters should be optimized by the BHA and MVO.

For creating the BHA-ANN and MVO-ANN hybrid models, the cost function of the metaheuristic algorithms should be defined to give the error through the ANN calculations. This function, therefore, needs to be minimized. To this end, the general equation of the determined ANN (fed by the training data) is given to the BHA and MVO. A proper optimization entails setting some parameters for these algorithms. The cost function, which calculates the error at each iteration, is defined to be root mean square error (RMSE) based on Eq. (6).

$$RMSE = \sqrt{\frac{1}{L}\sum_{i=1}^{L}(Z_{i_{observed}} - Z_{i_{predicted}})^2} \tag{6}$$

where L stands for the number of samples. Also, $Z_{i\ observed}$ and $Z_{i\ predicted}$ denote the expected and modeled SVs, respectively.

The number of iterations is another parameter that is set to 1000 for all models. Most importantly, the population size is a significant parameter in all swarm-based optimizers. Fig. 4 shows the optimization process.

In this work, the optimal value of the population size is found by a sensitivity analysis that challenges nine-different values (10, 25, 50, 75, 100, 200, 300, 400, and 500) of population size. Both BHA-ANN and MVO-ANN are

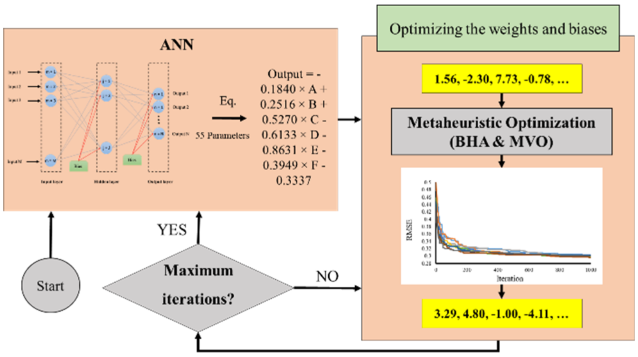


Fig. 4 Optimizing the ANN using metaheuristic algorithms

tested by these values and the convergence curves (showing the obtained RMSEs for all iterations) are shown in Fig. 5. As is seen, both algorithms have reduced the majority of error during the initial iterations. For both algorithms, the population size of 400 presented the most accurate optimization (RMSEs of 0.333571803 and 0.296794971 for the BHA and MVO, respectively).

Apart from the different optimization paths of the BHA-ANN and MVO-ANN, the time elapsed for finding the optimal solution is another important factor. Utilizing an Intel Core i7 64-bit operating system with 16 gigs of RAM, optimization by the BHO took around 11548 seconds, while this time was around 6331 seconds for the MVO.

3.2 Accuracy assessment criteria

As well as the RMSE, another error criterion, namely mean absolute error (MAE) is used to evaluate the accuracy of the models. The MAE is expressed by Equation 7. Moreover, the area under the receiving operating characteristic curve (AUROC) index is defined to measure the classification accuracy. The AUROC is a well-known indicator for the accuracy of classification problems (e.g., natural hazard occurrence prediction) (Swets 1988, Bui *et al*. 2019).

$$MAE = \frac{1}{l}\sum_{i=1}^{L}(Z_{i_{observed}} - Z_{i_{predicted}}) \tag{7}$$

3.3 Accuracy assessment of the predictive models

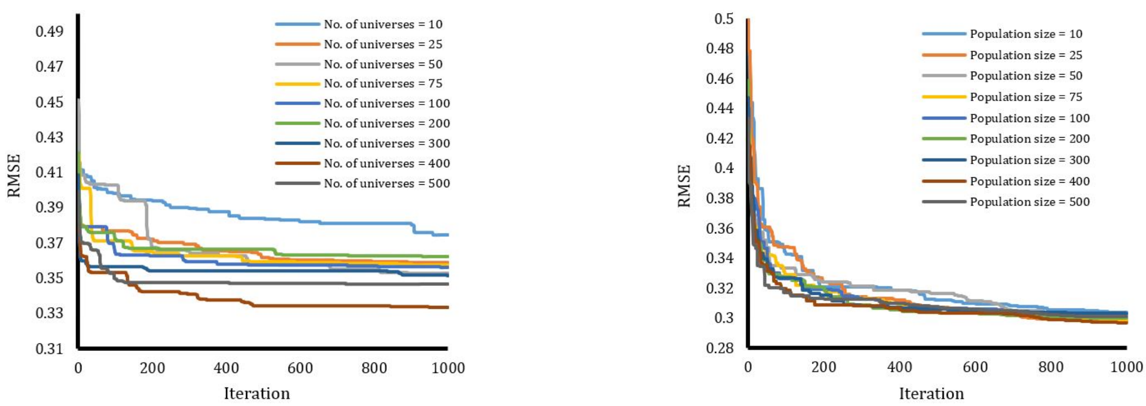
The SVs predicted by each model are compared with the expected ones (i.e., 0 and 1) to evaluate the learning and prediction accuracies. Fig. 6 presents the error values (= expected SV – modeled SV) obtained for training the ANN using the LM, BHA, and MVO algorithms. According to these figures, the training RMSE of the ANN is reduced from 0.3622 to 0.3335 and 0.2967 by functioning the BHA and MVO metaheuristic algorithms, respectively. It can be supported by the histogram charts which show the frequency of the error values. The MAE also experienced a significant reduction from 0.3204 to 0.2892 and 0.2412. From these values, it comes out that the BHA and MVO perform more efficiently than LM in training the ANN for inferring the relationship between the SV and system key factors.

Moreover, the ROC curves of the training data are illustrated in Figs. 7(a), (c), and (e). Based on these diagrams, the classification accuracy of the LM-ANN is increased from 94.0% to 96.3 and 97.2%. According to Figs. 7(b), (d), and (f) drawn for the testing data, the prediction accuracy of the LM-ANN rose from 93.1% to 94.4 and 95.0%. It indicates that the hybrid models have presented a more accurate approximation of the stability analysis.

Moreover, Table 2 addresses the calculated error criteria (i.e., RMSE and MAE) for the testing phase, along with the statistical parameters of the corresponding ROC curves. In comparison with the typically trained ANN, the lower RMSEs of the hybrid models (0.3789 vs. 0.3551 and 0.3273) demonstrate that the BHA-ANN and MVO-ANN can present a more reliable stability analysis. The obtained values of the MAE (0.3441 vs. 0.3135 and 0.2664) can support this claim.

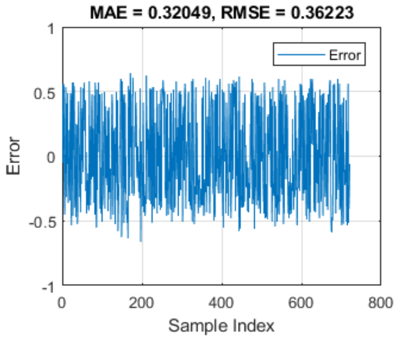
3.4 The SV evaluative formula

Regarding more than 94% accuracy in predicting the SV for unseen conditions, the applicability of the BHA-ANN and MVO-ANN models was demonstrated in the previous section. Now, based on the superiority of the MVO algorithm in constructing the ANN, the hyperparameters

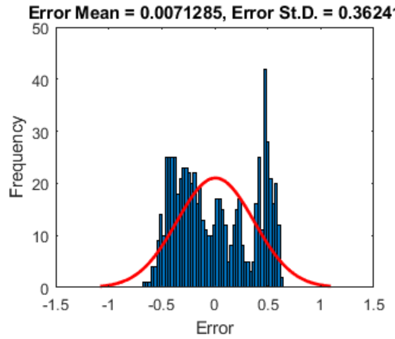


(a) BHA-ANN (b) MVO-ANN

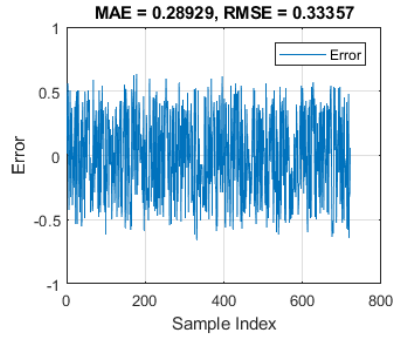
Fig. 5 Executed swarm-size sensitivity analysis



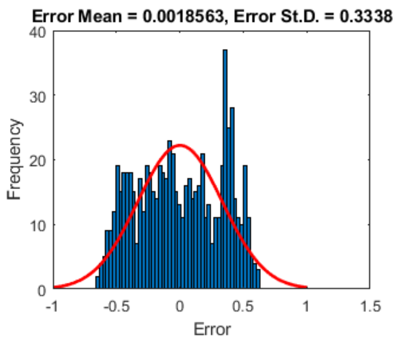
(a) LM-ANN



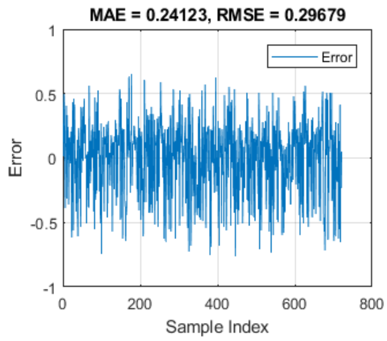
(b) LM-ANN



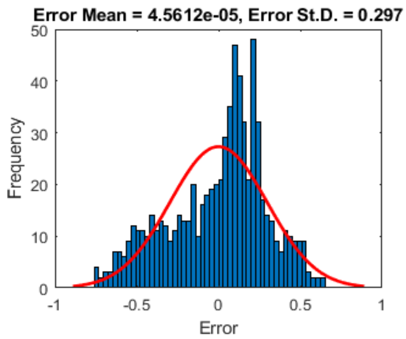
(c) BHA-ANN



(d) BHA-ANN

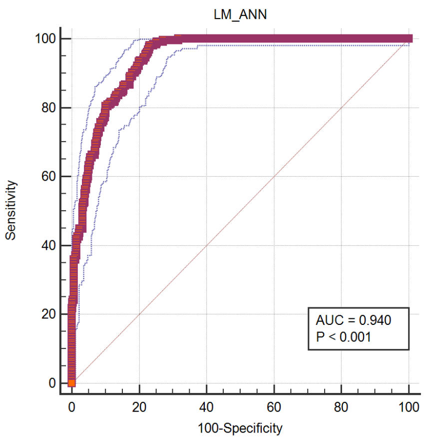


(e) MVO-ANN

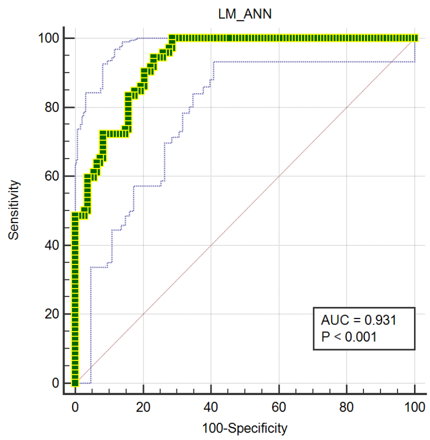


(f) MVO-ANN

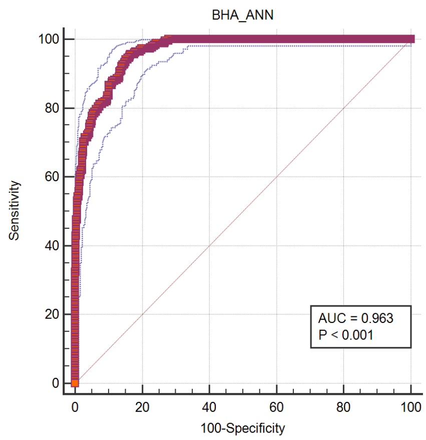
Fig. 6 The training results



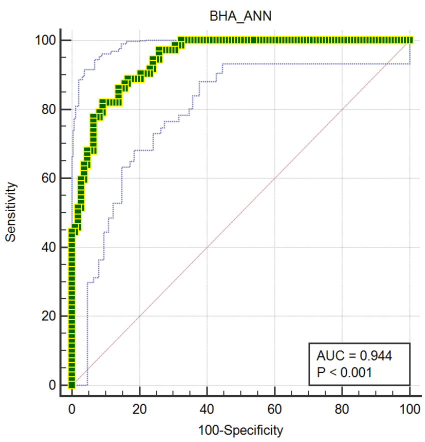
(a) LM-ANN training



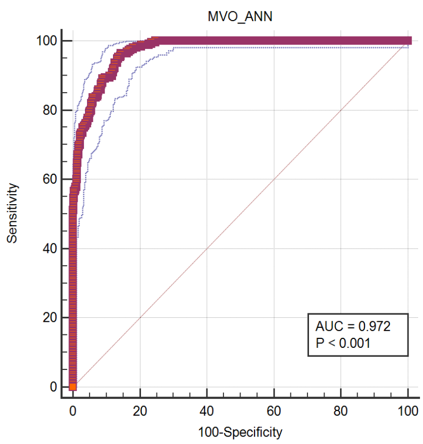
(b) LM-ANN testing



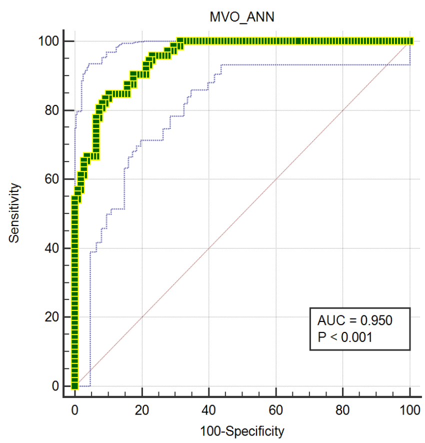
(c) BHA-ANN training



(d) BHA-ANN testing



(e) MVO-ANN training



(f) MVO-ANN testing

Fig. 7 The ROC curves

Table 2 A summary of the accuracy assessment

Criterion	Models		
	LM-ANN	BHA-ANN	MVO-ANN
RMSE	0.3789	0.3551	0.3273
MAE	0.3441	0.3135	0.2664
AUROC	0.931	0.944	0.950
Standard Error	0.0170	0.0150	0.0138
95% Confidence interval	0.883 to 0.963	0.900 to 0.973	0.908 to 0.977
Sensitivity	100.00	81.94	84.72
Specificity	71.30	90.74	89.81

suggested by this metaheuristic algorithm are arranged in the form of an SV predictive formula. Equation 8 releases the derided value through a simple and linear equation. But it should be noted that this formula needs to be fed by the outputs of Eq. (9) (i.e., A, B, C, D, E, and F). In other words, the numbers in these two equations represent the weights and biases of the ANN that are optimized by the MVO search scheme.

It was elucidated in section 3.1 that a total of 55 parameters compose this predictive formula. These values are suggested after being recursively optimized and adjusted by the optimization strategy of the MVO. It is expressed in Eq. (9) that 42 weights and 6 biases make the contribution between the inputs (i.e., *FA*, *DA*, *UW*, *EM*, *PR*, *SD*, and *AS*) and initial outputs of hidden neurons, and in Eq. (8), six weights and one bias make the contribution of initial outputs and global response.

Moayedi *et al*. (2019a) achieved the AUCs of 0.969, 0.964, 0.969, and 0.965 in the training phase, and 0.939, 0.935, 0.939, and 0.944 in the testing phase.

As is seen, the models used in this study can nicely compete with previously used colleagues. The MVO could outperform all models in both learning and predicting the bearing capacity behavior. The highest ACU obtained for this model indicates a dependable classification accuracy relative to other existing algorithms. The BHA could provide satisfying results, too.

From the time-efficiency point of view, the taken optimization time does not seem to be very high, but a more efficient solution may also be feasible in the future improved versions.

These studies have treated the bearing capacity problem from a classification point of view. In better words, they predicted the failure/stability of the system. This is while there are some other studies in which the problem has been solved by predicting the settlement values directly. Moayedi and Mosavi (2021) employed water cycle algorithm (WCA), electromagnetic field optimization (EFO), and shuffled complex evolution (SCE) for this purpose. It was shown that the combination of these algorithms with ANN can predict the settlement with around 90% correlation. They presented a formula based on the WCA-optimized network.

To sum up, the hybrid models in which ANN is trained by metaheuristic optimizers can be considered as reliable methodologies for dealing with the bearing capacity problem. Further efforts, in this regard, are recommended to focus on testing other algorithms to detect the most efficient tools. Also, simplifying the explicit formula obtained from such methods can be of interest

$$SV_{MVO-ANN} = -0.1840 \times A + 0.2516 \times B + 0.5270 \times C - 0.6133 \times D - 0.8631 \times E - 0.3949 \times F - 0.3337 \tag{8}$$

$$\begin{bmatrix} A \\ B \\ C \\ D \\ E \\ F \end{bmatrix} = Tansig\left(\left(\begin{bmatrix} -1.0580 & 0.3321 & -1.1260 & 0.2886 & 0.6520 & 0.2520 & -0.4481 \\ -0.4461 & -0.2951 & 0.2986 & -0.9712 & -0.9800 & -0.4810 & -0.8718 \\ 0.4605 & -0.0241 & -1.0182 & 0.6529 & -1.0488 & -0.1315 & 0.6909 \\ -1.0202 & -0.5136 & -0.1241 & -0.4504 & -1.1914 & 0.0474 & 0.5707 \\ 0.7990 & 0.9552 & -0.2028 & 0.6641 & 1.0529 & 0.0252 & 0.3578 \\ -0.7111 & -0.8229 & 0.6878 & -0.6732 & 0.8975 & -0.1078 & 0.5866 \end{bmatrix} \begin{bmatrix} FA \\ DA \\ UW \\ EM \\ PR \\ SD \\ AS \end{bmatrix}\right) + \begin{bmatrix} 1.8084 \\ 1.0850 \\ -0.3617 \\ -0.3617 \\ 1.0850 \\ -1.8084 \end{bmatrix}\right) \tag{9}$$

3.5 Comparison with literature

The BHA and MVO used in this work are among the powerful metaheuristic techniques that are capable of optimizing the ANN. The above results pointed out that the suggested hybrids can accurately deal with the bearing capacity problem.

In this section, the performance of the BHA and MVO is compared to the similar algorithms employed by other researchers for the same problem. As explained, the AUCs of BHA-ANN and MVO-ANN were 0.963 and 0.972 in the training phase, and 0.944 and 0.950 in the testing phase.

Moayedi *et al*. (2021), for instance, combined the ANN with Harris hawks optimization (HHO) and dragonfly algorithm (DA). The AUC values of the HHO-ANN and DA-ANN models were 0.944 and 0.968 in the training phase, and 0.915 and 0.942 in the testing phase. Likewise, the WOA, LCA, MFO, and ACO algorithms used by

3.6 Problem and solution

It is well known that many civil engineering issues require heavy calculations. Earlier, simulation techniques like finite elements could significantly handle these calculations. Recent advances in computer science and mathematics have led to the development of machine learning models which have been competent substitutes to traditional ones (Dede *et al*. 2019, Fathizadeh *et al*. 2021).

This study presented an application of machine learning for a challenging issue. In general, computations using machine learning are considerably more convenient, due to the fast, inexpensive, and efficient solutions provided. For instance, traditional approaches entail performing costly and time-consuming tasks like site investigations and laboratory efforts. Furthermore, utilizing finite element methods is associated with the necessity of providing assumptions, mesh grids, theoretical concepts, etc.

Apart from the advantages of the machine learning tools, the models of this study had another merit which was getting formed by an optimized solution. The use of MVO and BHA kept the ANN safe from issues like local minima.

However, the optimization process, owing to a large number of iterations, requires enough time. Hence, selecting a quick optimizer can cover this issue for good. Another appreciable subject can be optimizing the input parameters so as to reach a less complex problem space, and possibly, a more efficient solution. This optimization can be considered after the analysis presented in Fig. 3. Also, using metaheuristic algorithms for this purpose is another viable approach for feature validity.

4. Conclusions

Bearing capacity assessment has been a challenging task in civil engineering projects. The main focus of the current study was, therefore, to investigate the optimization capability of two novel metaheuristic techniques of black hole algorithm and multi-verse optimization in the field of bearing capacity analysis. The algorithms were used to find the optimal weights and biases of a neural network predictive model. The models were applied to predict the stability value for a two-layered soil system under a shallow footing. The results, first, showed that all three intelligent models can properly handle the assigned task. Second, the performance of the ANN was considerably enhanced by using the BHA and MVO optimizers. In this sense, the training error (MAE) was reduced by 9.74 and 24.72%, respectively. These values were 8.89 and 22.58% for the testing data. From a comparison point of view, it was derived that the MVO is more powerful than BHA in optimizing the ANN. Third, the BHA-ANN and MVO-ANN tested in this study (with 94.4 and 95.0% accuracy of classification) were superior to several similar hybrids applied to the same dataset. Lastly, the presented hybrid models can be reliably used for analyzing the bearing capacity in practice.

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