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ORIGINAL ARTICLE

Proposing two new metaheuristic algorithms of ALO-MLP and SHO-MLP in predicting bearing capacity of circular footing located on horizontal multilayer soil

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Abstract
In this study, for the issue of shallow circular footing's bearing capacity (also shown as F_{ult}), we used the merits of artificial neural network (ANN), while optimized it by two metaheuristic algorithms (i.e., ant lion optimization (ALO) and the spotted hyena optimizer (SHO)). Several studies demonstrated that ANNs have significant results in terms of predicting the soil's bearing capacity. Nevertheless, most models of ANN learning consist of different disadvantages. Accordantly, we focused on the application of two hybrid models of ALO–MLP and SHO–MLP for predicting the F_{ult} placed in layered soils. Moreover, we performed an Extensive Finite Element (FE) modeling on 16 sets of soil layer (soft soil placed onto stronger soil and vice versa) considering a database that consists of 703 testing and 2810 training datasets for preparing the training and testing datasets. The independent variables in terms of ALO and SHO algorithms have been optimized by taking into account a trial and error process. The input data layers consisted of (i) upper layer foundation/thickness width (*h/B*) ratio, (ii) bottom and topsoil layer properties (for example, six of the most important properties of soil), (iii) vertical settlement (*s*), (iv) footing width (*B*), where the main target was taken F_{ult}. According to RMSE and R^2, values of (0.996 and 0.034) and (0.994 and 0.044) are obtained for training dataset and values of (0.994 and 0.040) and (0.991 and 0.050) are found for the testing dataset of proposed SHO–MLP and ALO–MLP best-fit prediction network structures, respectively. This proves higher reliability of the proposed hybrid model of SHO–MLP in approximating shallow circular footing bearing capacity.

Keywords SHO–MLP · ALO–MLP · ANN · Optimization · Circular footing

1 Introduction

In recent years, to perform the prediction of circular footing bearing capacity (F_{ult}) in particular soil environments as well as in other complex engineering matters, scholars have introduced artificial neural networks (ANN) or a combination of

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ANN with metaheuristic algorithms [1, 2]. For soil mechanics and geotechnical engineering, investigating the term F_{ult} of foundations (i.e., the maximum considered stresses, related to a pre-defined settlement of equal to 0.10 B, which B refers to foundation width) is essential. Moreover, the term F_{ult} (e.g., complex geological structures) is yet well understood. Traditional approaches (e.g., techniques includes extensive experimental efforts [3–5] or limit equilibrium consideration [4, 6]) are usually based on performing complex mathematical-based solutions. In numerous studies, the introduced approaches showed how the thickness of the top layer and also its ratio towards the footing width influence the F_{ult} of the shallow footings (e.g., located on two or sometimes more soils). In this way, the bearing capacity along with a settlement of shallow footings are based on many major parameters such as, (1) the properties of soil layers under the footing (2) factors revealing strength characteristics of foundation, and finally (3) the footing shape. Adding layers of soil under the footing can increase the problem complication. For calculating the soil bearing capacity (for example, for a special settlement) of circular, and square footings, various relations were suggested [7–9]. In terms of predicting the F_{ult}, after real stresses, minimizing the likelihood of high settlement is known as the main concern. The most impressive factors in the case of computing a correction value for the bearing capacity were : (1) arrangement of soil layers, (2) footing shape (for example, strip, rectangular and circular), and (3) layered soils beneath footing or soil factors [10]. The soil properties including, unit weight, internal friction angle and cohesion, and dilation angle as well as Poisson's ratio elastic modulus can generate stresses for the footing. Generally, the F_{ult} was specified as the highest considered stress in the case of the maximum settlement ratio of 0.1 ($S/B=0.1$ of the footing width) [6, 11]. Bearing capacity for the shallow footing can be affected by various factors like multilayer soil condition, footing width, geological condition, type of the soil, failure model attended via the predictions and location of the stronger soil such as soil layer arrangement [12]. In many studies, for presenting a more reliable and verify calculation for the F_{ult}, (Gao et al. [13], Latifi et al. [14] and Uncuoglu [15] and Ahmadi and Kouchaki [16]), scholars suggested and proposed formulas.

In the present work, we have assessed 24 hybrid structures along with 72 ANN models to enhance the performance of ANN algorithm to provide a better performance result, namely (1) spotted hyena optimizer (SHO) as well as (2) ant lion optimization (ALO) which were designed for forecasting the F_{ult} of the circular footing. The provided hybrid models of SHA–MLP and ALO–MLP are not used in the engineering-based instance of this work. There is no investigation performed on the use of the suggested models for estimating the circular footing F_{elt} placed on multilayer conditions of the soil. In addition, we have optimized the algorithm of the ANN algorithm along with two hybrid models of OA to have a more reliable estimation of F_{ult} rested on soils that are layered.

2 Artificial intelligent systems

2.1 Multilayer perceptron

As proposed in the present work, three distinct artificial intelligent systems (i.e., following multilayer perceptron (MLP) techniques) are utilized namely, (1) hybrid ALO–MLP, (2) SHO–MLP, and (3) conventional feedforward backpropagation ANN for estimating the F_{ult} placed on a multilayer soil condition. For the first time, McCulloch and Pitts [17] suggested the ANN. In this way, the first method for training ANNs is proposed in Ref. [18]. There exist many rules based on hypotheses as well as observations of neuro-physiologic nature. Based on biological neurons, many scholars studied the development of simple and nonlinear mathematical models [18–22]. They generated a large number of structures (for example, topologies) along with network learning algorithms [22–25]. Models that are based on ANN approaches train a network and also evaluate the predicted outcome along with a predefined testing dataset [26, 27]. The details of the ANN-based solution are shown in Fig. 1. The structure of ANN in the prediction of vertical settlement is shown in Fig. 2.

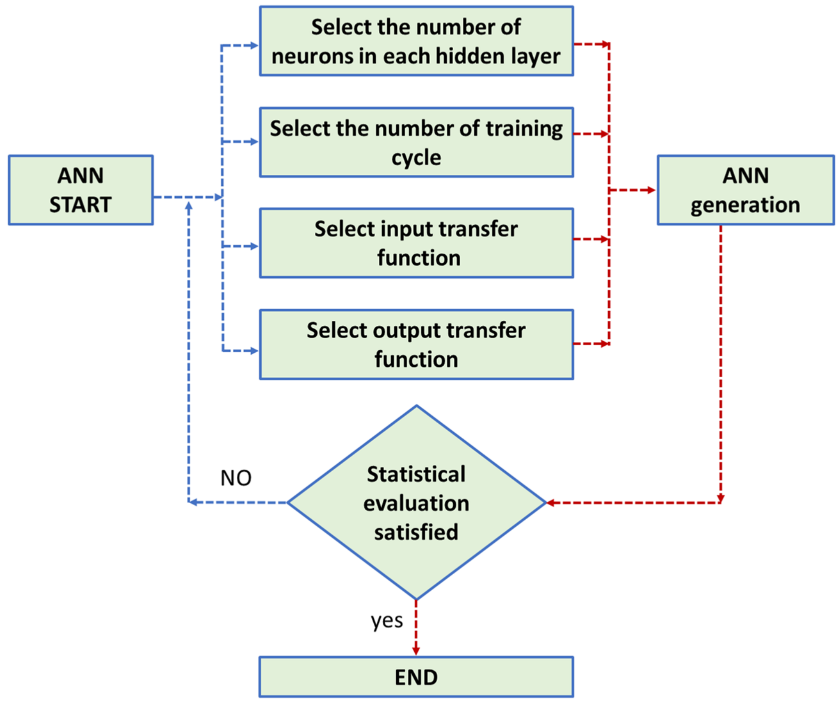
2.2 Ant lion optimization

Mirjalili [28] expanded the algorithm of ant lion optimization (ALO) as a novel capable metaheuristic approach, imitating the herding conduct of ant lions. In this algorithm, in the existing search space, important placements of the ant lions and target hunt have to be defined, stochastically. For each model repetition, it consists of six main steps as follows:

(1): Accidental walk of prey, (2) trapping in holes, (3) making a trap, (4) the sliding the prey to the ant lion, and (5) taking the prey/building the hole and (6) specifying the elite ant lion.

The first step and the hunting conduct of antlions can be seen in Fig. 3. The prey fitness helped the hunting ability of the ant lions because, in this approach, each hunter can hunt only one prey. For this reason, a function, namely roulette wheel selection (RWS) is utilized. In addition, details of the mathematical optimization process and the ALO have been detailed in previous studies as in [29, 30].

Fig. 1 Scheme of ANN-based solution



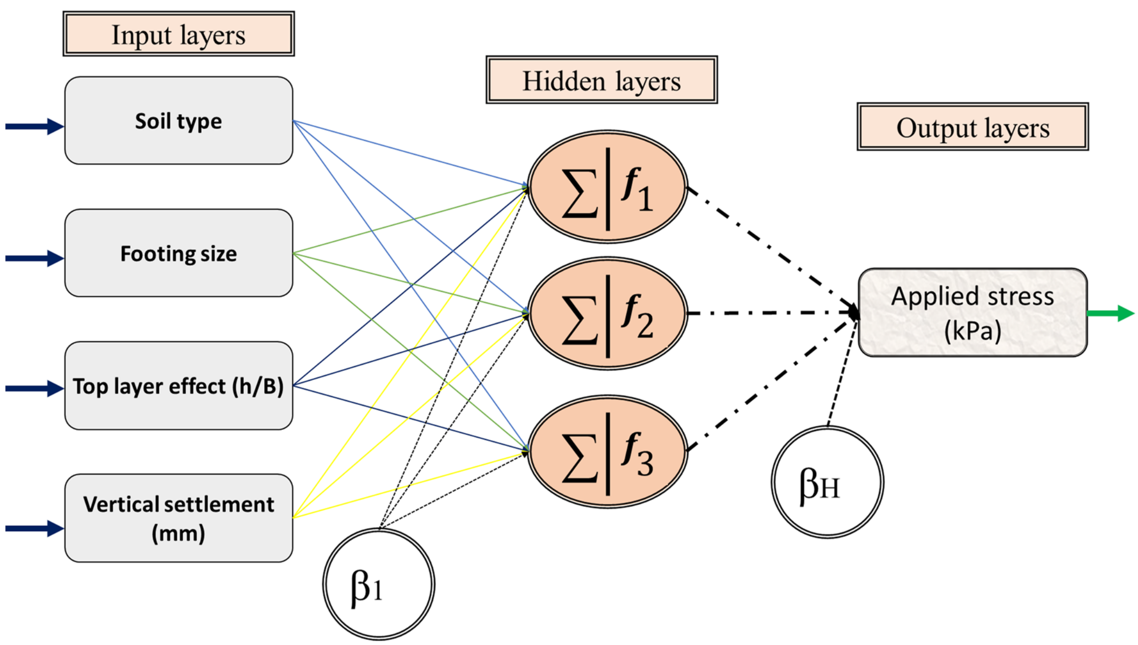


Fig. 2 The MLP structure utilized in this study

2.3 Spotted hyena optimizer

The spotted hyena optimizer (SHO), which is suggested by Dhiman and Kumar [16], is a newly developed optimization approach. It was inspired by an observation of the hunting conduct of the spotted hyena. They are social animals, which commonly hunt and always live in groups. The most important steps of the mentioned approach, which are searching and encircling prey, attacking prey, and other searching conducts of spotted hyenas, are shown in Fig. 4. As the search zone is not a priority for them, the most significant candidate solution intended to be optimized [16]. In this approach, it was supposed that the prime search agent recognizes the prey place and others have to update their

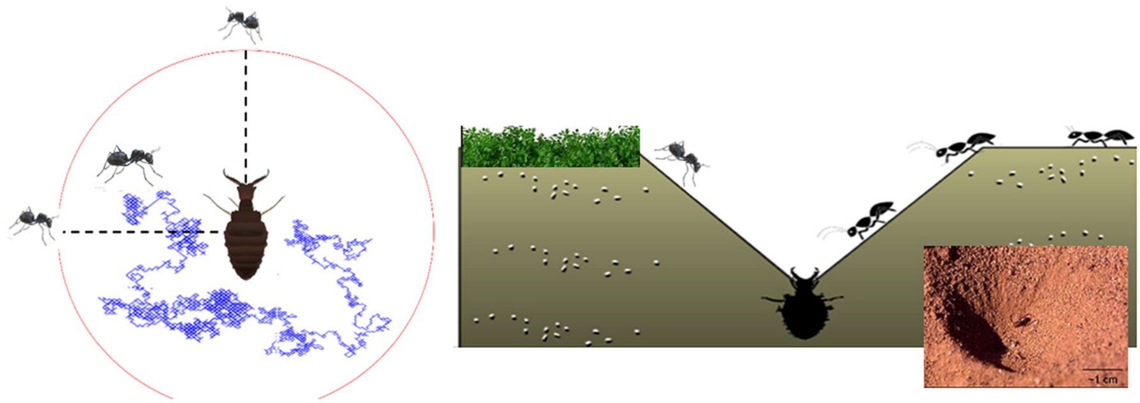


Fig. 3 **a** Random walk in the case of the prey in the trap, and **b** the antlions hunting conduct

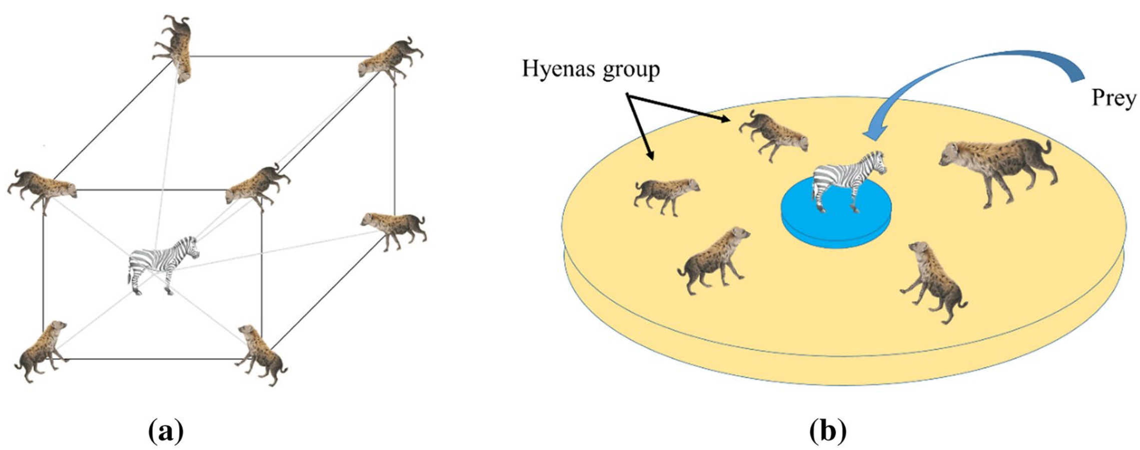


Fig. 4 Hunting algorithm performed in the algorithm of spotted hyena optimizer (SHO): **a** the feasible next places of the members along with position vectors, and **b** attacking the prey

positions with creating a cluster (trustworthy group) near the elite agent. For more information around the ruling relations in terms of the SHO, please refer to the Refs. [31–33].

2.4 Hybrid ALO–MLP and SHO–MLP

To improve the performance of the MLP-based models and to utilize an optimized version of ALO–MLP and SHO–MLP algorithms, numerous attempts have been performed. In this regard, the genetic-based algorithms are the most known optimization algorithms in terms of solving engineering problems. Moreover, for removing the weakness of the ANNs utilizing algorithms of optimization, many studies were done. The optimized searching approach of the ANN algorithm can lead to an unsatisfactory solution because the backpropagation is known as a local searching system, for example searching via the training algorithm. To enhance the performance of optimization algorithms, their initial MLP-based interface is optimized in terms of bias and weight values. Hence, by utilizing hybrid systems like ALO-MLP and SHO-MLP, the weakness of the ANN approach to find the global minimum can be eliminated (e.g., enhancement of its searching properties with fitness functions and cost functions) [34–37]. In the present paper, SHO and ALO search for the global minimum after normalization of both training and testing datasets. The ANN can be used for discovering the finest network prediction outcomes of the systems.

3 Data collection

In the present work, eight different soil types with a significant distinction in their basic properties were utilized. These properties reveal the most usual kinds of sands. In the modeling, internal dilation and friction angles that are in ranges of 3.4–11.5 and 32–42 degrees, respectively, are selected and used. Moreover, we determined that the unit weight, Poisson's ratio, and elastic modulus varied between 19 and

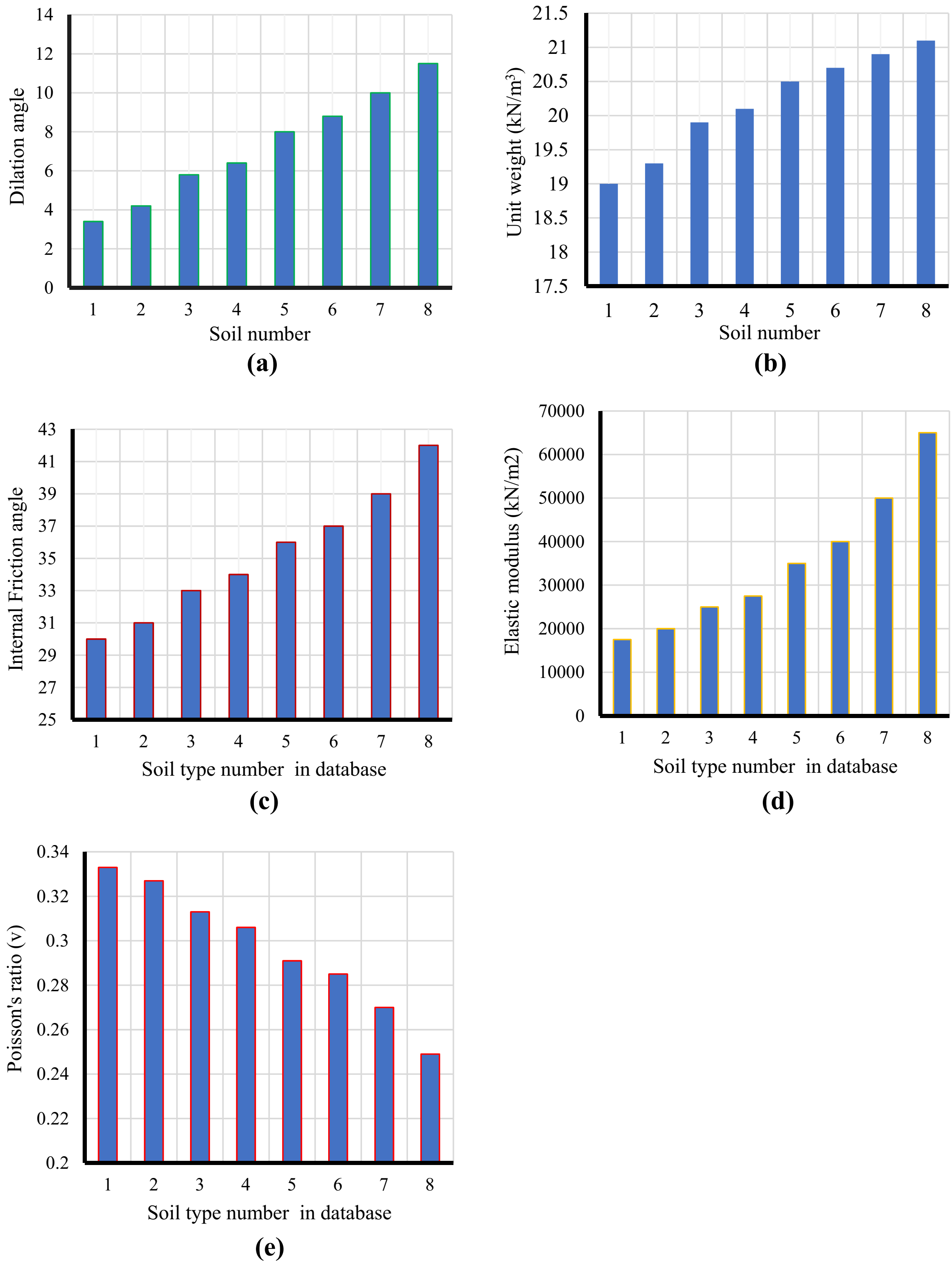


Fig. 5 A range summary of input data against soil type

21.1 kN/m^3, 0.333–0.249, and 17500–65,000 kN/m^2, respectively. The soil properties that are utilized in network estimation are denoted as a set of the graphical summary that is the range of input information. As can be seen in Fig. 5, these datasets consist of elastic modulus, friction angle, and unit weight, and also Poisson's ratio. Asymmetric FEM for circular foundation (e.g., a width equal to 1.0 m) rested on two-layer of soils (refer to Fig. 6) to identify considered stresses

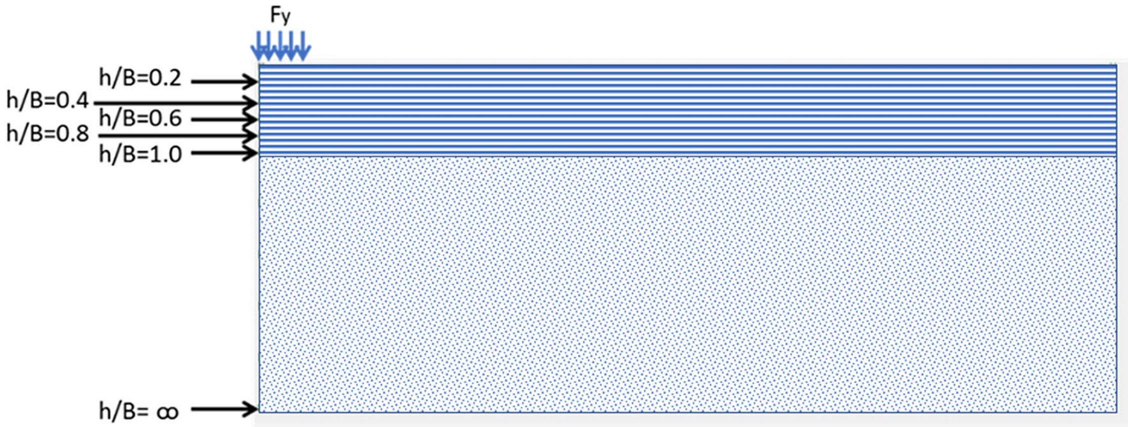


Fig. 6 A view of the FEM model

beneath the footing. The soil layers under the foundations are commonly not homogeneous in practical civil engineering projects. Note that there exist many instances that the (1) stronger soil rested onto a layer of soil that is much weaker physical properties or (2) a weaker layer of soil placed on the stronger layer of soil. For estimating the properties' impacts of soil layer on ultimately applied stresses, we used Plaxis 2D that is a commercial finite element software. According to many recommendations (for example, Mosallanezhad and Moayedi [38], and Hou et al. [39]), the most effective parameters, which influence the bearing capacity of the soil is (1) soil primary characteristics (e.g., Elastic modulus, Friction angle, Poisson's ratio, dilation angle, unit weight, the thickness of the soil layer under the footing, and also maximum expected settlement (s)). To estimate the F_{ult} in a two-layered sandy soil, cohesion is considered to be zero. It is noted that zero values for cohesion (i.e., soil without any cohesive strength) provide sandy soil conditions and for the upper layer width of thickness or foundation, values of 0, 0.4, 0.4, 0.8 and 1.0 are utilized.

To produce the best-fit structure in the case of the suggested above-mentioned metaheuristic algorithm, the database used for training the models was achieved through 3513 full-scale finite element simulations. The database is provided to a circular footing with a 1-m radius, placed on two-layered soil conditions. It is important to state that the amounts of vertical stress before gaining the maximum S/B ratio were labeled F_{ult}. As proposed in the previous studies (Anvari and Shooshpasha [40], Noorzad and Manavirad [41]), we selected upper layer width of thickness or foundation (h/B), internal friction angle (φ), soil dilation angle (ψ), soil elastic modulus (E), Poisson's ratio (v), unit weight of the soil (γ), and prescribed vertical settlement (s) as main input layers and utilized datasets to create the suggested hybrid structures.

4 Model development

4.1 Initial network optimization

The main objective of the present work is to estimate the maximum used stress onto circular footings rested in 16 distinct layered soil conditions. The most appropriate structure in the case of the model of ANN can be achieved after an extensive number of trial and error processes and also by changing the number of hidden layers along with a number of neurons [42, 43]. Hence, a total of seventy-two ANN-*Tansig* models are constructed. To find their best performances of a network, the performance of all ML-based proposed networks was evaluated. Nevertheless, as shown in Figs. 7 and 8, after checking all network performance with 8 hidden neurons, better network performance results are gained. It shows the best-fit ANN structure, should have a $4 \times 6 \times 1$ structure. However, looking to the trivial change in the network performance and the accuracy for both of the training and testing datasets (as can be seen in Figs. 7, 8), respectively, the optimal amount for the pre-specified number of nodes in an individual structure of hidden layer is determined to be six. It is also a simplification that makes the proposed model more practical.

4.2 Hybrid ALO–MLP and SHO–MLP models

For selecting the most appropriate predictive model among two hybrid models of ALO–MLP and SHO–MLP, we utilized both of them. Thus, many parametric studies are conducted to specify optimum factors in both models. An optimized version of ANN architecture requires to be specified prior to conducting a parametric study of hybrid model parameters. Investigating the model of ANN is done by taking into account a set of trial and error approaches. We determined that an algorithm of ANN by the architecture of

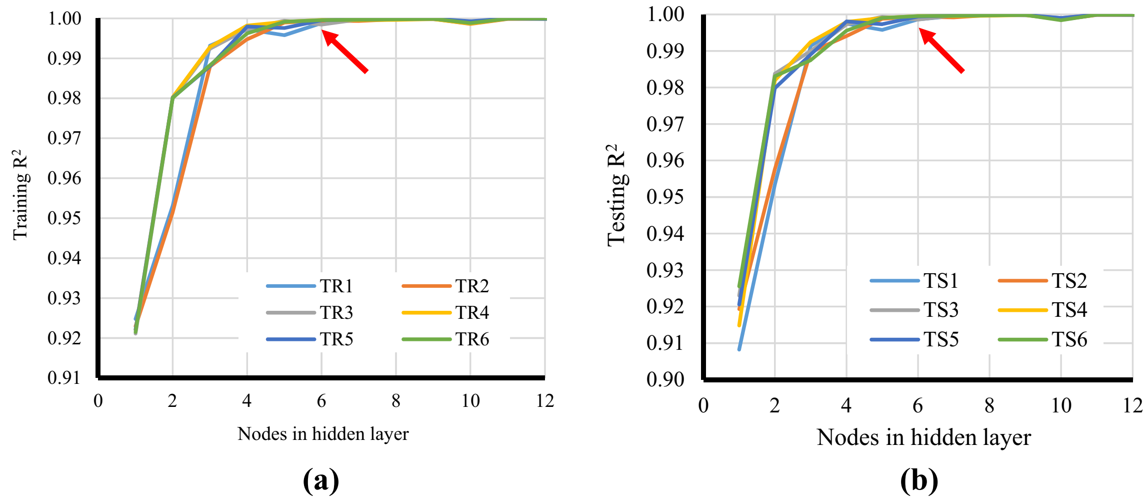


Fig. 7 R^2 variation against the nodes number in terms of the prediction of bearing capacity

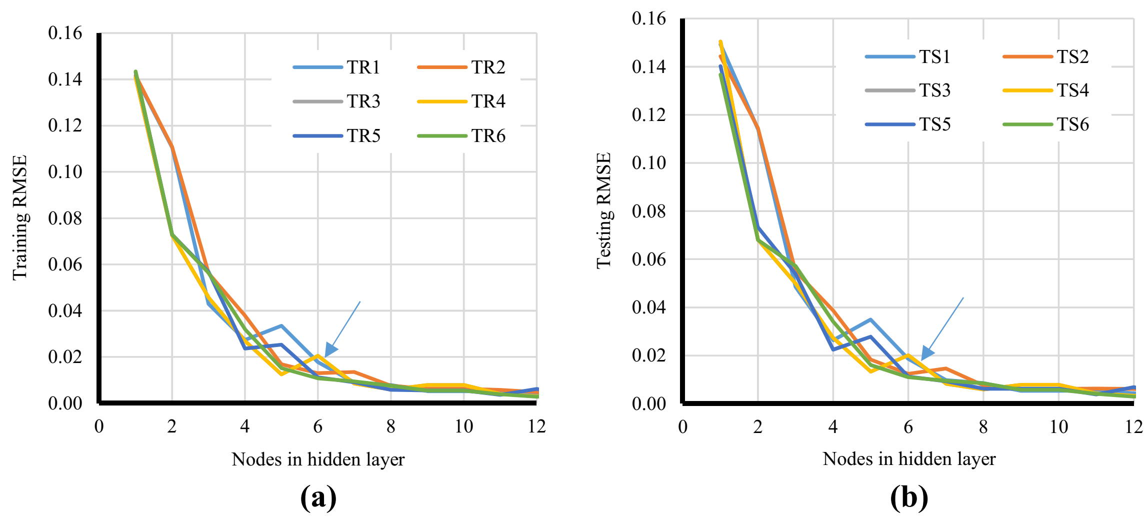


Fig. 8 RMSE variation against the nodes number in terms of the prediction of bearing capacity

$4 \times 6 \times 1$ or eight hidden neurons provided more appropriate performances. Therefore, the created architecture is verified and utilized for hybrid intelligent systems, ALO–MLP and SHO–MLP. The variation of performance results (e.g., MSE used here) of ALO–MLP and SHO–MLP models with various population sizes is shown in Figs. 9 and 10, respectively.

To obtain the best predictive outcome from the SHO–MLP and ALO–MLP models, optimizing their most influential parameter is an important concern. The optimization of the predictive capacity of hybrid ALO–MLP and SHO–MLP model needs a series of error and trial progress like the first parametric investigation approach performed, for example selecting best-fit ANN architecture. Accordingly, several models were designed using different values of population size 25, 50, 75, 100, 150, 200, 250, 300, 350, 400, 450 and 500. The results varied largely based on the changes in the initial parameters. For instance, in the SHO–MLP, the training R^2 were 0.986, 0.987, 0.993, 0.993, 0.993, 0.993, 0.991, 0.986, 0.989, 0.992, and 0.996, respectively, for the swarm size equal to 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500. On the contrary, the accuracy of predictions through SHO–MLP changed considering variation in the ALO–MLP structure (Table 1). For example, the training ALO–MLP-RMSE were 0.105, 0.082, 0.054, 0.077, 0.063, 0.045, 0.050, 0.058, 0.047, 0.066, and 0.044 for the swarm size equal to 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500, respectively (Table 2).

Several approaches of SHO are made by taking into account different numbers of swarm sizes, i.e., 50, 100, 200, 300, 400 and 500. According to their performance

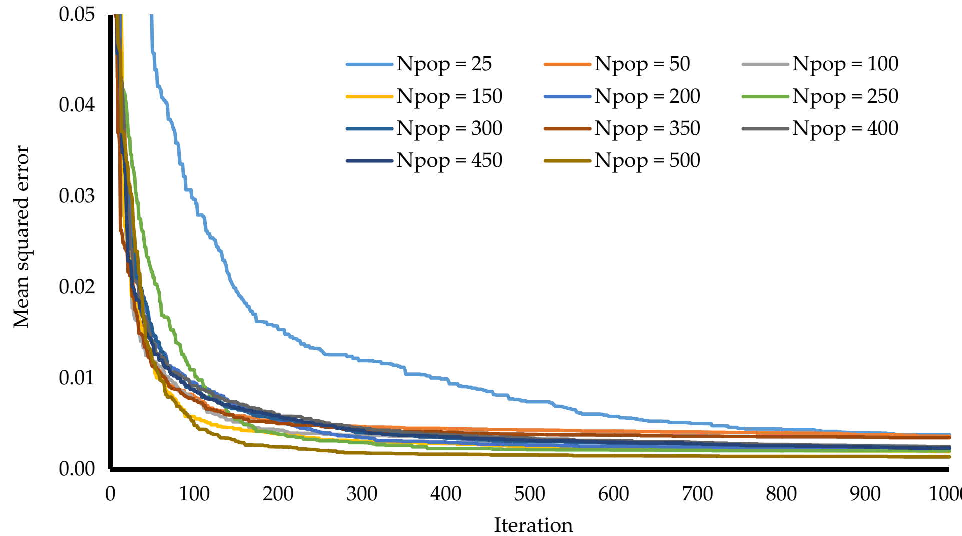


Fig. 9 SHO–MLP models with different population sizes

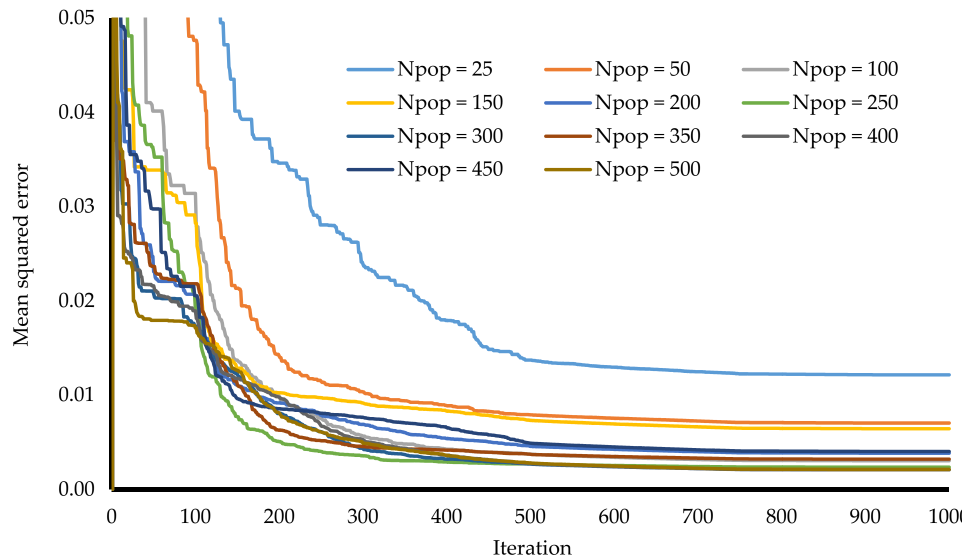


Fig. 10 ALO–MLP models with different population sizes

Table 1 Network results for various SHO–MLP models

Population size	Network result				Ranking				Total rank	Rank
	Train		Test		Train		Test			
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE		
25	0.986	0.059	0.988	0.061	2	2	4	2	10	10
50	0.987	0.062	0.972	0.064	3	1	1	1	6	11
100	0.993	0.048	0.989	0.051	8	5	5	8	26	5
150	0.993	0.042	0.993	0.051	7	10	10	9	36	2
200	0.993	0.045	0.986	0.060	9	8	2	3	22	7
250	0.993	0.042	0.991	0.053	10	9	7	6	32	4
300	0.991	0.048	0.991	0.052	5	6	8	7	26	5
350	0.986	0.058	0.986	0.058	1	3	3	4	11	9
400	0.989	0.056	0.991	0.053	4	4	6	5	19	8
450	0.992	0.047	0.992	0.034	6	7	9	11	33	3
500	0.996	0.034	0.994	0.040	11	11	11	10	43	1

Table 2 Network results for various ALO–MLP models

Population size	Network result				Ranking				Total rank	Rank
	Train		Test		Train		Test			
	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE		
25	0.951	0.105	0.954	0.104	1	1	1	1	4	11
50	0.974	0.082	0.982	0.082	2	2	5	3	12	9
100	0.990	0.054	0.982	0.071	8	7	4	4	23	7
150	0.975	0.077	0.971	0.088	3	3	2	2	10	10
200	0.972	0.063	0.977	0.065	5	5	3	5	18	8
250	0.993	0.045	0.993	0.045	10	10	11	10	41	1
300	0.990	0.050	0.990	0.052	7	8	9	8	32	4
350	0.985	0.058	0.987	0.054	6	6	7	6	25	5
400	0.991	0.047	0.989	0.052	9	9	8	7	33	3
450	0.982	0.066	0.972	0.044	4	4	6	11	25	5
500	0.994	0.044	0.991	0.050	11	11	10	9	41	1

indices, RMSE and R^2, these models are also evaluated. It was determined that enhancing the number of nodes leads to higher convergence among the measured and estimated network results. It is found that the model with 500 swarm size is the best value in comparison to other values. Training and testing outcomes of selected models, i.e., SHO–MLP (Table 1) and ALO–MLP (Table 2) in predicting shallow footing bearing capacity settled on the multilayered sandy environment. Based on their R^2, are presented in Figs. 11 and 12, respectively.

Training and testing results of the SHO–MLP and ALO–MLP model in predicting shallow circular footing bearing capacity are shown in Figs. 11 and 12, respectively. Overall, it can be seen that the SHO–MLP is superior to the other proposed hybrid technique of ALO–MLP. The best-fit structure for the SHO–MLP and ALO–MLP is found when the swarm size was equal to 500.

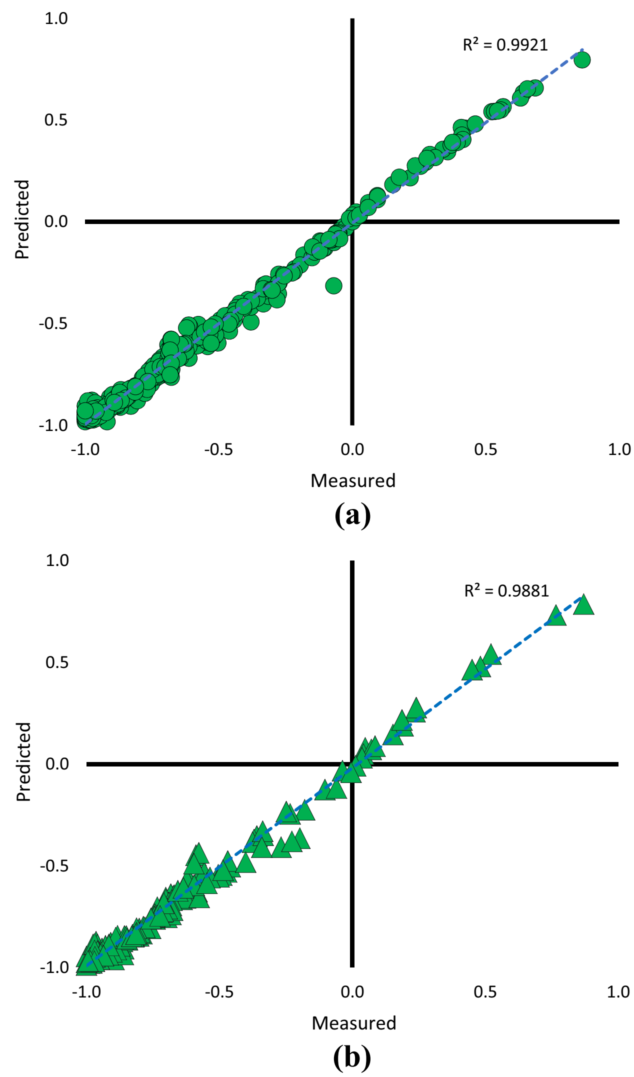


Fig. 11 Training and testing outcomes obtained by SHO–MLP model in terms of predicting shallow circular footing bearing capacity

5 Conclusions

For measuring the applicability of the presented approach, results of a total of 3513 FEM simulations were employed. The learning approach was appropriate almost in all suggested models. Although, suggested models have satisfactory approximation outcomes in estimation of circular shallow footing bearing capacity, settled on a horizontal multilayer soil stratum, the hybrid SHO–MLP model (i.e., a combination of MLP optimized with SHO) can be presented as a more reliable ANN approach for this purpose. This is because the suggested SHO-MLP models presented higher performance outcome in terms of proposed statistical indexes (for example, R^2 *and RMSE*) for both of the training and testing stages. This can be obviously observed from the

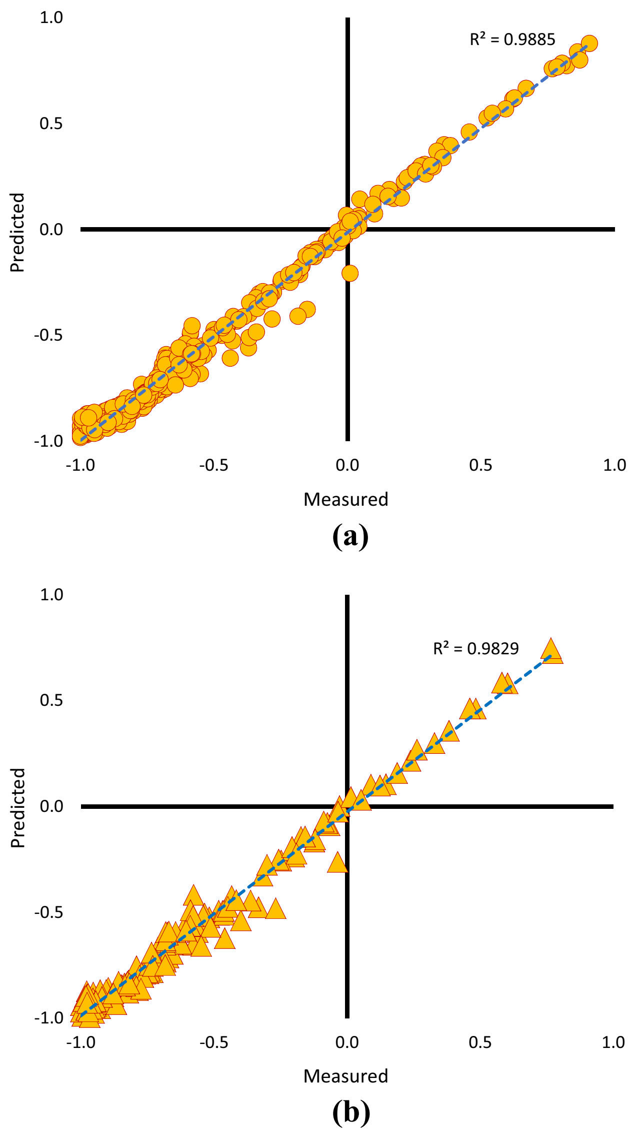


Fig. 12 Training and testing outcomes obtained by ALO–MLP model in terms of predicting shallow circular footing bearing capacity

high-performance outcomes of the training as well as the testing network. Based on R^2 results of testing dataset, and considering the population size equal to 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500, values of (0.988, 0.972, 0.989, 0.993, 0.986, 0.991, 0.991, 0.986, 0.991, 0.992, and 0.994) as well as (0.954, 0.982, 0.982, 0.971, 0.977, 0.993, 0.990, 0.987, 0.989, 0.972, and 0.991) were calculated for the SHO–MLP and ALO–MLP predictive networks, respectively. This shows the superiority of the best-fit hybridized SHO–MLP structure (i.e., with swarm size equal to 500) in the estimation of circular footing bearing capacity.

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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