

Four novel evolutionary computational models to estimate piles' bearing capacity

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(Received December 14, 2023, Revised February 25, 2025, Accepted March 8, 2025)

Abstract. Accurate pile-bearing capacity prediction is crucial for ensuring the stability and safety of deep foundations, particularly for tall buildings. This study investigates the use of four hybrid evolutionary computational models — Whale Optimization Algorithm (WOA), Artificial Bee Colony (ABC), Ant Colony Optimization (ACO), and Ant Lion Optimizer (ALO) — to enhance prediction accuracy. These models were evaluated for training and testing datasets based on their population sizes and performance metrics, such as the coefficient of determination (R^2) and root mean square error (RMSE). The WOA model demonstrated the highest accuracy, achieving an R^2 of 0.979 (training) and 0.968 (testing), along with RMSE values of 0.079 and 0.11, respectively. The ALO model followed closely, with an R^2 of 0.989 (training) and 0.968 (testing), though it showed a higher RMSE in testing at 0.235. ABC and ACO, with R^2 values ranging between 0.883 and 0.958, displayed lower accuracy than WOA and ALO. The models were ranked based on their performance, with WOA obtaining the highest total rank, followed by ALO, while ABC and ACO shared a similar total rank. These findings highlight the potential of hybrid evolutionary models for improving pile-bearing capacity predictions, which is vital for geotechnical engineering applications.

Keywords: driven piles; hybrid; nature-inspired; predicting; shaft friction capacity

1. Introduction

A huge area of study is represented using artificial intelligence (AI) approaches to solve complex problems, which has recently attracted a vast deal of interest in geotechnical engineering (Li *et al.* 2022). The reason is the capability of these techniques to find complex nonlinear relations among various parameters (Wu *et al.* 2022). Several assessments have been performed on utilizing the artificial neural network (ANN) to estimate the lateral load capacity of piles (Noureldin *et al.* 2023), bearing capacity of the pile foundation, efficiency of pile groups installed in sandy soil, pile settlements, utilizing SPT-based techniques for estimating the bearing capacity of driven piles, driven piles in cohesionless soils, and base resistance of open-ended piles (Liang *et al.* 2005, Park and Cho 2010, Xia *et al.* 2010, Ismail and Jeng 2011). A wide database of pile driving records was reanalyzed by Goh (1996), utilizing neural networks to assess the feasibility of utilizing artificial

intelligence computation for predicting the driven piles' load-bearing capacity. Therefore, it was found that the neural network predictions had more reliability and consistency compared to the other conventional pile-driving formulas. Che *et al.* (2003) used the artificial neural network to predict the axial capacity of driven piles at Macao. They presented a back-propagation (Zhang *et al.* 2021) neural network model for estimating the pile-bearing capacity (Zhao *et al.* 2023). The driven pile features and dynamic stress wave data achieved the pile's bearing capacity. The findings revealed satisfactory accuracy in the neural network model predicting toe and shaft resistance. A hybrid genetic algorithm and neural network method were generated by Park *et al.* (2006) to estimate the driven piles' bearing capacity. A support vector machine (SVM) was applied by Samui (2008) to predict the friction capacity of driven piles in clay. The SVM results were compared with those of previously published artificial neural network models. Consequently, good performance was found for the SVM model, indicating better performance than the present artificial neural network models. The evaluation approaches for the ultimate bearing capacity of the driven pile were assessed by Tian and Wei (2009). The authors used the hyperbolic function to analyze four empirical approaches. The consolidation theory system was ultimately suggested to predict the time-based ultimate hearing capacity for the single-driven pile. The model proposed by Park and Cho (2010) included data from both tip and shaft components of the field dynamic load test's driven piles. The findings

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revealed that the proposed hybrid model could be a reliable and simple predictive tool for the concrete-driven piles' bearing capacity (Han *et al.* 2001). Shahin (2010) used intelligent computation approaches to the model axial capacity of pile foundations (Jang 2022). To develop a novel ANN model and provide axial capacity predictions with higher accuracy, comprehensive data were collected from previous studies, including 94 drilled-shaft load and 80 driven pile tests and CPT results. The performance of the CPT methods and ANN models was translated into various simple design equations suitable for hand calculations to facilitate the utilization of the present ANN models. Samui (2011) used multivariate adaptive regression spline (MARS) to assess the driven piles' friction capacity in clay. It was indicated that the MARS was an adaptive nonparametric regression method. The input variables for the MARS model included undrained shear strength, pile length, pile diameter, and effective vertical stress. The friction capacity was the output. A comparison was made between the findings of the presented MARS model and the ANN results. Thus, the established MARS model was robust enough to predict the friction capacity in driven piles mounted in clay. Samui performed similar work with the same method on the cohesionless soil (Samui 2012). A novel technique was developed by Milad *et al.* (2015) to predict the driven piles' bearing capacity. An equation was presented through genetic programming and linear regression based on the soil parameters, pile geometries, and flap number to determine the pile-bearing capacity. Ultimately, the accuracy of the three proposed models was compared. The Toe-bearing capacity of pretension spun high-strength concrete (PHC) driven piles in the sand was predicted by Hung *et al.* (2016) utilizing various CPT-based techniques. This work used 82 piezocone penetration tests and 190 pile-driving analyzers to analyze the reliability. Ultimately, an evaluation was performed on the performances of some CPT-based techniques. Using artificial intelligence methods, Suman *et al.* (2016) predicted the friction resistance of driven piles in clay. The prediction models were established utilizing two presently developed artificial intelligence methods, MARS and functional networks (FN). The models predicted the friction resistance of piles in clay soils based on various experiments. The statistical performances revealed FN and MARS models with better predictive resistance than the present models.

One of the primary issues with foundation settlement in tall buildings is differential settlement, where different parts of the structure settle at varying rates (Chen 2020). This can result in cracks, tilting, or even structural failure. Ensuring that all piles are seated in uniform and stable soil layers is essential to minimize this risk. Piles must be designed to transfer loads to deeper, more stable soil or rock strata to prevent excessive or uneven settlement (Shen *et al.* 2021). If different piles settle at different rates, it can lead to internal stresses in the structure, causing damage over time. Settlement can directly affect the accuracy of models predicting the bearing capacity of piles (Ren and Sun 2023). The predictions could be overly optimistic if the underlying soil is not uniform or the models do not account

for potential settlement. This could lead to an underestimation of pile movement and overall foundation performance. Prediction models should integrate settlement behavior, mainly focusing on how different soils compress under load. Including such variables as soil stratification, compressibility, and time-dependent settlement characteristics can improve the reliability of the models (Alkhdour *et al.* 2023). Predictive models often rely on the assumption that the underlying conditions are homogenous. However, variability in soil conditions can lead to non-uniform settlement. Enhancing the models to account for soil variability and potential differential settlement can lead to more accurate and resilient designs. A key consideration in minimizing foundation settlement is ensuring piles are driven or bored to consistent depths and anchored into uniform, stable soil or rock layers (Fernandes *et al.* 2020). This ensures that all piles settle uniformly, reducing differential movement. In large, tall structures, piles work together as a system. Uneven settlement can occur if the load distribution among piles is not adequately accounted for in the design. Therefore, predictive models should simulate group effects, ensuring the load is evenly distributed among piles (Alimohammadi 2024). Evolutionary computational models, which rely on optimization algorithms, can be adapted to factor in settlement data by refining parameters related to soil properties and pile-soil interaction (Boumezerane 2022). This can lead to better predictions and allow the models to evolve and improve based on real-world settlement behavior. Incorporating historical settlement data from similar structures into the computational models can help improve accuracy (Pepi *et al.* 2021). These data can guide the evolutionary process of model refinement, ensuring the models better account for settlement risks. To improve the reliability of evolutionary computational models for pile bearing capacity estimation, it's crucial to incorporate considerations of foundation settlement into the model. This can be done by integrating factors like soil variability, settlement behavior, and load distribution into the predictions. Addressing these concerns will lead to better designs, ensuring that pile foundations perform optimally and minimize the risks associated with uneven settlement in tall buildings.

This paper proposes a paradigm shift by harnessing the power of neural evolutionary classification techniques. These methods are designed to improve the accuracy and reliability of bearing capacity predictions by leveraging both neural networks and evolutionary algorithms. The first method under scrutiny is the Artificial Bee Colony Algorithm (ABC) (Chicoine *et al.* 2002, Zhang *et al.* 2019). The foraging behavior of honeybees inspires ABC and has been widely applied in optimization problems. In the context of this research, ABC will be adapted to fine-tune the neural network's classification capabilities. By mimicking bees' collaborative and intelligent foraging process, ABC offers the potential to discover optimal solutions that may have remained elusive through conventional methods. Khanmohammadi *et al.* (2022) presented a workable approach that considers the impacts of time following the conclusion of pile driving for the

preparation and optimization of pile-bearing capacity. Using a genetic programming (GP) model, the prediction phase suggests an intelligent equation. Therefore, the following factors were thought to be predictors of pile bearing capacity: pile shape, soil qualities, starting pile capacity, and time after driving completion. An adequate degree of accuracy in determining pile bearing capacity was offered by the established GP equation. During the optimization phase, the highest bearing capacity of the pile—which equates to the ideal values for input parameters—was obtained by feeding the developed GP equation into two potent optimization algorithms, the artificial bee colony (ABC) and the grey wolf optimization (GWO). GWO outperformed the ABC algorithm in terms of pile capacity among these two algorithms.

The Whale Optimization Algorithm (WOA) is the second method to be investigated. WOA draws inspiration from the hunting behavior of humpback whales (Mirjalili and Lewis 2016). WOA's adaptability and ability to balance exploration and exploitation make it a promising candidate for optimizing the neural network's classification performance. The research will delve into how WOA can be harnessed to enhance the precision of piles' bearing capacity predictions and its applicability to geotechnical engineering problems. Nguyen *et al.* (2023) offered a hybrid model to estimate the bearing capacity of concrete piles by fusing the whale optimization algorithm (WOA) with the extreme gradient boosting machine (XGBoost). The XGBoost gives the final prediction from a collection of variables from an explanatory experiment. The WOA contributes to the accuracy and resilience of the model by searching for the ideal collection of XGBoost parameters. A dataset including 472 samples gathered from static load testing conducted in Vietnam is used to build the hybrid approach. The results reveal that the hybrid model regularly beats the default XGBoost model and deep neural network (DNN) regression. In comparison to the DNN with 2, 3, 4, and 5 hidden layers, the suggested model has achieved around 12, 11.7, 9, and 12% decreases in root mean square error over the course of 20 repetitions of the experiment.

The third method, Ant Lion Optimization (ALO), is modeled after the foraging strategy of antlion larvae. ALO's unique approach to optimization involves the creation of trap-like structures that capture prey. In the context of this study, ALO's ingenuity will be channeled toward enhancing the neural network's classification capabilities. ALO's capacity to trap and refine solutions may prove advantageous in fine-tuning predictions (Liu *et al.* 2021). To address the bearing capacity of shallow circular footing (also represented as Fult), two metaheuristic algorithms—ant lion optimization (ALO) and the spotted hyena optimizer (SHO)—were employed in conjunction with the benefits of artificial neural networks (ANNs). Numerous investigations have shown that artificial neural networks (ANNs) can accurately forecast the carrying capacity of soil. However, the majority of ANN learning models have a variety of drawbacks. Accordingly, Liu *et al.* (2021) concentrated on using two-hybrid ALO-MLP and SHO-MLP models to predict the Fult in layered soils. Moreover, Liu *et al.* (2021) used a database of 703 testing and 2810

training datasets to prepare the training and testing datasets. They conducted an extensive finite element (FE) modeling on 16 sets of soil layers (soft soil placed onto more robust soil and vice versa). A process of trial and error has been used to optimize the independent variables for the ALO and SHO algorithms. The input data layers included the following: (i) the ratio of the upper layer foundation/thickness width (h/B), (ii) qualities of the bottom and topsoil layer (such as six of the most significant soil properties), (iii) vertical settlement (s), and (iv) footing width (B), where Fult was the primary aim. The training dataset yields values of (0.996 and 0.034) and (0.994 and 0.044) according to R^2 and RMSE. In contrast, the testing dataset of the suggested SHO-MLP and ALO-MLP best-fit prediction network architectures yields values of (0.994 and 0.040) and (0.991 and 0.050), respectively.

The fourth and final method, Ant Colony Optimization (ACO), emulates the foraging behavior of ants in search of optimal paths (Dorigo and Di Caro 1999). ACO has been extensively applied to optimize problems and network routing. In this research, ACO will be explored to optimize the classification process of the neural network, aiming to achieve more accurate predictions of piles' bearing capacity (Mirjalili 2015). Assareh and Poultangari (2023) attempted to calculate the pile settlement rates using pile samples. Because of this, a novel hybrid model was employed in a framework that combined the employment of an Ant Colony Optimization (ACO) and Grey Wolf Optimization (GWO) with a Radial Basis Function Neural Network (RBFNN). Optimizers are used to determine the ideal number of neurons in the hidden layer of an RBFNN. Using a hybrid RBF-GWO and RBF-ACO algorithm, Malaysia's Kuala Lumpur transportation network was examined to look at pile movement dependent on ground conditions and attributes. The performance of each framework was assessed using the indices. Consequently, the MAE displayed the rates of 0.2583 and 0.3386, respectively, while the R^2 's of RBF-GWO and RBF-ACO obtained values of 0.5176 and 0.6562, respectively. The RBF-GWO appropriate accuracy was also demonstrated by the correlation R -value, which was 1.23 percent greater than that of another model. Therefore, results have implied that the RBF-GWO's performance is desirable for estimating PS. Table 1 lists current research on the subject of this paper:

The consequences of documented load tests and conventional limit equilibrium theories on driven piles are available. However, a limited quantity of information exists in the literature on designing the driven piles in clay. The present design methods for driven piles are primarily complex, not representing accurate and reliable recommendations in clay. Several factors affecting the piles' behavior make the problem even more complicated. The available approaches oversimplify the nature of the problem. Therefore, the present study aimed to discover a reliable mathematical equation for predicting the driven pile's friction capacity in clay. Moreover, the effect of essential parameters on friction capacity was investigated, including the primary factors leading to appropriate derived pile design, the effectiveness of pile diameter, undrained

Table 1 Recent studies on the topic of this article

References	Case study subject	Method	Error analysis
(Ren and Sun 2023)	Bearing capacity of pile foundation	APSO	$R^2 = 0.9854$
		AGA	0.9772
(Kumar <i>et al.</i> 2023)		PSO	$R^2 = 0.9773$
		GP	0.9854
(Kumar <i>et al.</i> 2022)		ANFIS-PSO	$R^2 = 0.85$
(Amjad <i>et al.</i> 2022)		XGBoost	$R^2 = 0.955$
(Momeni <i>et al.</i> 2014)		GA-ANN	$R^2 = 0.990$
(Pham <i>et al.</i> 2020)		ANN	$R^2 = 0.866$
		RF	0.866
(Shaik <i>et al.</i> 2019)		ANN	0.905
	ICA-ANN	$R^2 = 0.958$	
	ANFIS	0.975	

cohesion, pile length, and effective vertical stresses on pile friction capacity, as well as establishing precise design charts to design the driven pile in clay.

2. Established data

When designing piles for high-rise buildings, several critical factors must be addressed to ensure structural integrity and performance such as; (i) *Load-Bearing Capacity*: Piles must be designed to support the loads from the building, which includes the dead load (weight of the structure), live load (occupants and furniture), and any additional loads like wind or seismic forces. The type of soil plays a significant role in determining the pile capacity. (ii) *Soil Conditions*: The geotechnical properties of the soil, such as its bearing capacity, density, moisture content, and permeability, directly affect pile design. Site investigations are crucial to understanding soil stratigraphy and determining the appropriate pile type (e.g., friction piles, end-bearing piles). (iii) *Pile Material*: The selection of pile material (concrete, steel, or timber) depends on the environment, soil conditions, and load requirements. Concrete piles are often preferred for high-rise structures due to their durability and load-bearing capabilities. (iv) *Settlement Control*: Excessive settlement can lead to differential movement and structural issues. Piles must be designed to limit settlement, which is especially critical for high-rise buildings where even small movements can cause structural problems. (v) *Pile Length and Diameter*: Pile length is typically determined by the depth at which suitable bearing strata are found. The pile diameter is selected based on load requirements and the available construction techniques. Longer piles may be needed in soft or loose soils to reach deeper, more stable layers. (vi) *Seismic Considerations*: Pile piles must be designed to withstand earthquake forces in areas prone to seismic activity. This may involve using seismic load combinations and ensuring ductility in pile design to absorb energy during ground shaking. (vii) *Corrosion Protection*: For piles exposed to water or aggressive soil conditions (e.g., in coastal areas), corrosion protection is essential. This might involve using coatings, cathodic protection, or corrosion-resistant

materials. (viii) *Construction Constraints*: The type of pile installation (e.g., driven, bored, or helical piles) is influenced by site accessibility, noise restrictions, and proximity to other structures. The installation process should minimize disturbances to the surrounding soil to prevent settlement or damage to nearby structures.

For the development of prediction models for vertical capacity of piles, data-set of Goh (1996) has been used in this study. The database consists of in-situ test on soil and maintained pile load test data from different parts of the world. A Maintained Pile Load Test (MPLT) is a method used to assess the load-bearing capacity and behavior of piles under applied loads. It is one of the most reliable ways to verify that piles can support the design loads without excessive settlement or failure. The data collected from this test provides crucial information for pile design and construction decisions. The MPLT has three main goals including (i) To determine the maximum load a pile can safely carry. (ii) To monitor how much settlement occurs under different load increments. (iii) To understand how the load is transferred through the pile to the surrounding soil or rock (through friction, end-bearing, or both). Note that the maximum test load applied is often 1.5 to 2 times the design load. The database includes pile diameter (cm), pile length (m), undrained shear strength (S_u), and effective vertical stress (S_v). In this sense sixty-five in-situ tests were conducted to generate the datasets. The inputs layers that chosen among the parameters that influence the output most. The pile's bearing capacity is set to be the target in the present work. Fig. 1 shows an instance of the output and input dataset utilized in ANN modeling.

3. Methods

Here, the utilized methods are presented and discussed. Whale optimization algorithm (WOA), ant colony optimization (ACO), ant lion optimization (ALO), and artificial bee colony algorithm (ABC) were the models employed. Eighty experimental observations were gathered from the developed databases and utilized for training and testing the models above. As previously expressed, estimating a driven pile's friction capacity was the primary

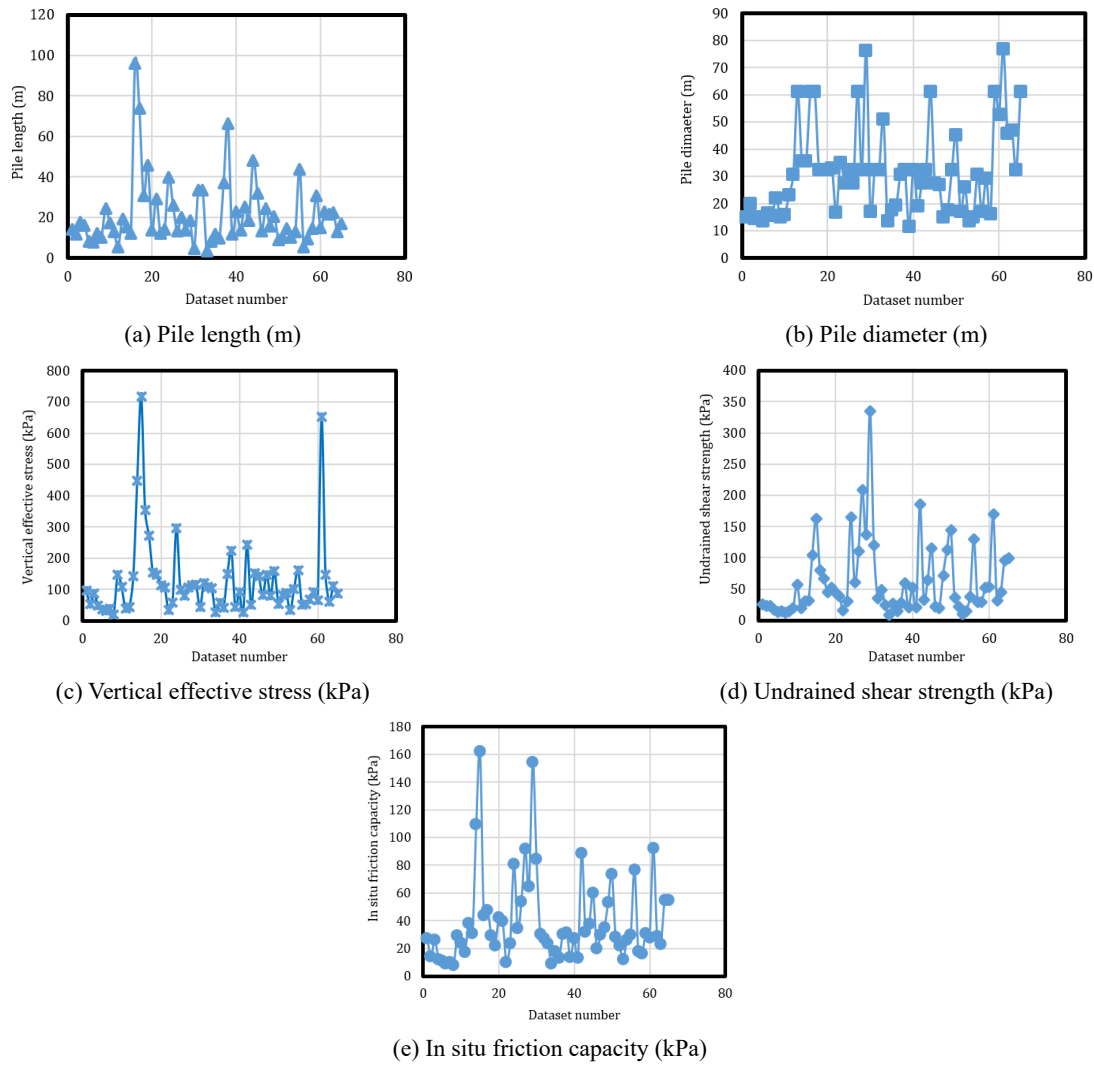


Fig. 1 Inputs and outputs parameters

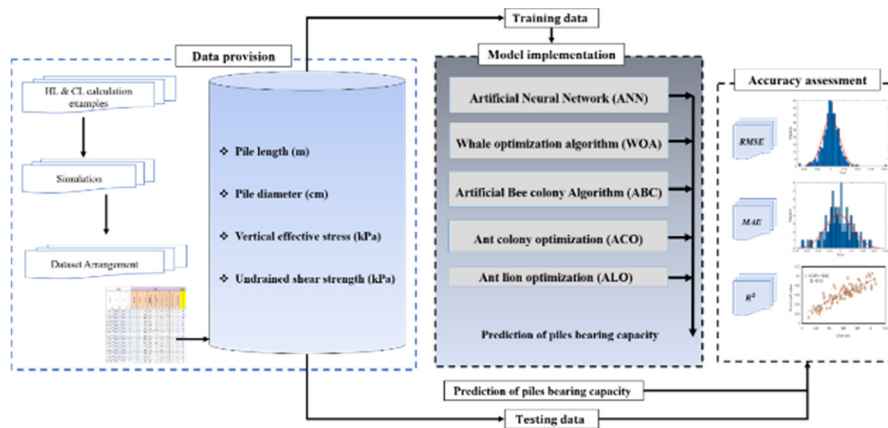


Fig. 2 Research flowchart including input parameters to predict the shaft friction capacity output

goal. Fig. 2 shows the flowchart of the current study.

3.1 Artificial neural network

McCulloch and Pitts introduced the artificial neural network (ANN) (McCulloch and Pitts 1943). By models

based on ANN, the information is processed in a training network, and the network output is evaluated by randomly selecting the testing dataset (Güneyisi *et al.* 2014). By developing and creating the ANN, complicated systems can be modeled in every science in estimation problems (Hakim and Razak 2013). As an interconnected multilayer structure,

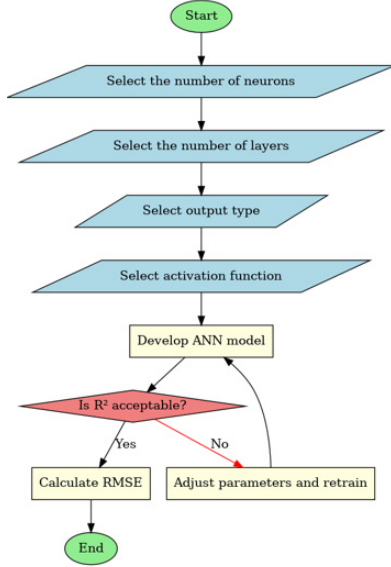


Fig. 3 A general flowchart for the ANN models

it comprises numerous neurons. This network can identify similarities, particularly with novel input terms followed by a predicted output pattern appropriately (Alnaqi *et al.* 2019, Moayedi *et al.* 2020). The details of the ANN algorithm are shown in Fig. 3.

3.2 Whale optimization algorithm (WOA)

The term whale optimization algorithm (WOA) represents a novel metaheuristic method based on the humpback whales' bubble-net hunting trend (Fig. 4) (Mirjalili and Lewis 2016). It is a swarm-based intelligent method to solve complex optimization issues with continuous domain (Nasiri and Khiyabani 2018, Trivedi *et al.* 2018). In the swarm, the whales pursue their prey in a multidimensional space. The position of each relation is represented as the decision variable, in which the cost function is determined as the distance between each whale and the prey location. The following operational steps can be taken to evaluate the time constraint function as a position for the whales (Mirjalili and Lewis 2016, Rana and Abd Latiff 2018):

- Lessening surrounding hunt,
- Exploitation stage (the bubble-net attacking)
- Exploration stage (looking for the prey).

As seen in Fig. 5, by recognizing the location of the presented prey, it is encircled by the humpback whales by moving in 9 forms. WOA remarks on the target prey as the most suitable candidate solution (or near the elite solution) since it possesses no data about the prey's optimum position within the searching zone. It considers the possible attempts to discover the elite search agent. Remarkably, other included relations try to update their locations near the elite one.

$$\vec{D} = |C * \vec{X}^*(t) - \vec{X}(t)| \quad (1)$$

$$\vec{X}(t+1) = \vec{X}^*(t) - A \cdot \vec{D} \quad (2)$$

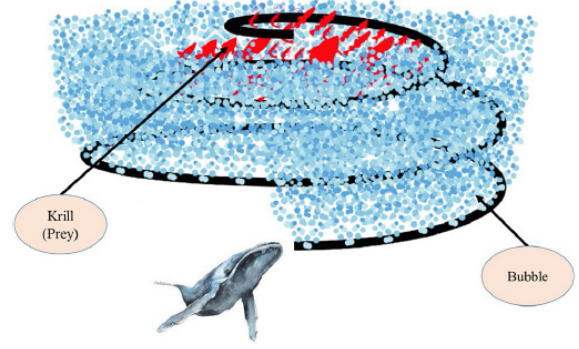


Fig. 4 The humpback whales' bubble-net feeding

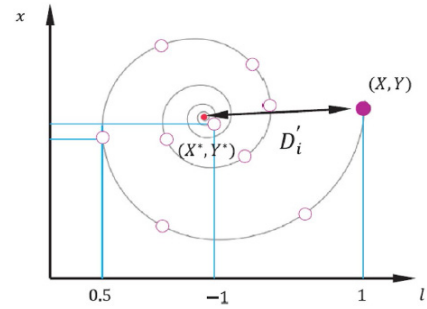


Fig. 5 The spiral updating process

$$A = 2 \cdot a \cdot r - a \quad (3)$$

$$C = 2 \cdot r \quad (4)$$

where \vec{X} represents the whale's location, \vec{X}^* shows the universal elite position, and t denotes the recent try. Also, a is linearly reduced from 2 to 0, and r represents a random number equally distributed between 0 and 1. These phases are:

Exploitation:

The WOA algorithm's bubble-net hunting performance is presented in Fig. 6. The equidistance between the locations of the prey and the whale is perceived using a spiral mathematical method. The whale's location (in a helix environment) should be set after moving (Kaveh 2017)

$$\vec{X}(t+1) = e^{bk} \cdot \cos(2\pi k) \cdot \vec{D}' + \vec{X}^*(t) \quad (5)$$

$$\vec{D}' = |\vec{X}^*(t) - \vec{X}(t)| \quad (6)$$

where k and b represent arbitrary and constant numbers, notably, b denotes the logarithmic spiral shape, and k is equally distributed within -1 to 1 .

3.2.2 Exploration

As seen in Fig. 7, when $A < -1$ or $A > 1$, the search agent is upgraded by a randomly chosen member at the elite agent's position as

$$\vec{X}(t+1) = \vec{X}_{rand} - A \cdot \vec{D}' \quad (7)$$

$$\vec{D}'' = |\vec{C} \cdot \vec{X}_{rand} - \vec{X}(t)| \quad (8)$$

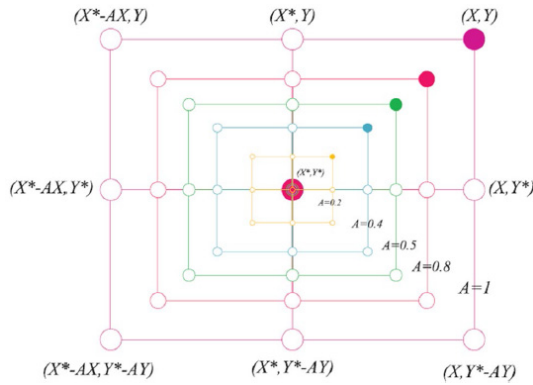


Fig. 6 Exploitation phase

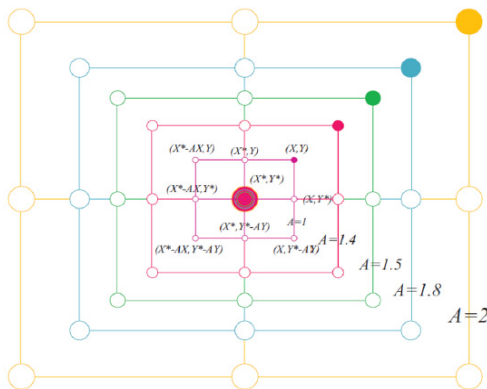


Fig. 7 Exploration phase

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Initialize the whales population  $X_i$  ( $i = 1, 2, \dots, n$ )
Calculate the fitness of each search agent
 $X^*$  = the best search agent
while ( $t <$  maximum number of iterations)
  for each search agent
    Update  $a$ ,  $A$ ,  $C$ ,  $l$ , and  $p$ 
    if1 ( $p < 0.5$ )
      if2 ( $|A| < 1$ )
        Update the position of the current search agent by the Eq. (4)
      else if2 ( $|A| \geq 1$ )
        Select a random search agent ( $X_{rand}$ )
        Update the position of the current search agent by the Eq. (10)
      end if2
    else if1 ( $p \geq 0.5$ )
      Update the position of the current search by the Eq. (8)
    end if1
  end for
  Check if any search agent goes beyond the search space and amend it
  Calculate the fitness of each search agent
  Update  $X^*$  if there is a better solution
   $t = t + 1$ 
end while
return  $X^*$ 
    
```

Fig. 8 The pseudocode of the WOA algorithm

where $\vec{C} \cdot \overrightarrow{X_{rand}}$ rand represents the whales arbitrarily for the presented iteration (Mirjalili and Lewis 2016). Fig. 8 shows this algorithm's pseudocode.

3.3 Artificial bee colony algorithm (ABC)

The artificial Bee Colony (ABC) algorithm is based on natural bees' social behavior (Karaboga 2005). Like other optimization algorithms, a society of artificial bees is made at the first stage, comprising scout bees, employed bees, and onlooker bees (Chicoine *et al.* 2002, Zhang *et al.* 2019).

They are then randomly located in the search zone representing the food sources' location (Degertekin 2012, Dokeroglu *et al.* 2019). There are two phases in the foraging procedure. First, the scout bees find a new food source in the exploration phase (Aydin *et al.* 2015). Second, the scout bees act as employed bees, agitating the next neighbor randomly in the exploitation phase. Thus, a correction can be made to the solution saved in the bee's memory. Then, the amount of nectar in the newly discovered source (as a new solution) is assessed. The bee notes the new location, and the old one is passed up when it includes more nectar than the former. Further details have been provided on this algorithm in the literature (Karaboga *et al.* 2007, Nguyen *et al.* 2019b).

3.4 Ant colony optimization (ACO)

ACO was first presented in 1999 by Dorigo and Di Caro (1999). Since then, it has become popular as one of the extensively utilized swarm optimization algorithms in the machine learning and statistical community. The ACO is mainly based on stigmergy in nature (Mirjalili 2019), in which, using environmental manipulation, the members communicate with each other through unique environmental manipulation. To achieve the best local connection, they need to move closer to this unique communication method (Dorigo *et al.* 2000). The members (i.e., ants) constantly search for food sources around their nests in ACO. They find the food and mark their pathways with a distinctive pheromone symbol (Dorigo and Stützle 2019). However, the quantity of pheromones is highly based on the quality and quantity of the food source. Including a higher concentration of pheromones indicates that the pathway results in extra high-quality food (Nguyen *et al.* 2019a). Based on the pheromone's attention, the route to the maximum quality food source can be found by other ants, bringing them back to their nest. More interestingly, ants could count and remember their phases accurately. Thus, they can discover the shortest or most optimum pathway based on the pheromone concentration. Fig. 9 shows the pseudocode of the ACO algorithm. The ants' paths and the pheromone quantity and their flowchart are represented in Fig. 10. The ants' paths and the amount of the resultant pheromone are also represented (Fig. 10). Considering the pheromone amount, ants can understand the optimum path based on the flowchart (Fig. 10(b)). Therefore, it is essential to consider the number of ants or populations. Then, a global search is run by the ants for the state. When the state is understood as the final one, pheromones are deposited as a unique sign for other ants. Otherwise, other states are searched by the ants to continue. Finding the final state leads to daemon activities to make the pheromone dispersion. The other ants can recognize the marked state based on the pheromone evaporation.

3.5 Ant lion optimization (ALO)

The ant lion optimization (ALO) algorithm was expanded by Mirjalili (2015) as a new metaheuristic approach. It imitates the ant lions' herding behavior. In this algorithm, important ant lions and target hunt placements

Algorithm: The pseudo-code of the ACO algorithm

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(1) Input: Instance  $x \in I$  of  $\Pi_{opt}$ 
(2) Set algorithm parameters ()
(3)  $i, j \leftarrow 0$ 
(4) For  $j=1$  to colonies do
(5)    $Ant\ s_j \leftarrow$  creat sub-colony and release
(6)   Agent
(7)   While not-termination conditions
(8)     On sub-colony do
(9)        $i = i+1$ 
(10)      Manage_ants activity ()
(11)      Manage_Pheromone ()
(12)      Manage_Daemon Action ()
(13)      Selection Procedure ()
(14)      Compute solution quality ()
(15)    End while
(16)     $j = j+1$ 
(17)     $S_{best} \leftarrow$  candidate to be optimal solution
(18)    Update pheromone on arc ()
(19)  End for
(20) Output:  $S_{best}$  "candidate" to be the best found solution  $x \in I$ 

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Fig. 9 Pseudocode for the ACO algorithm

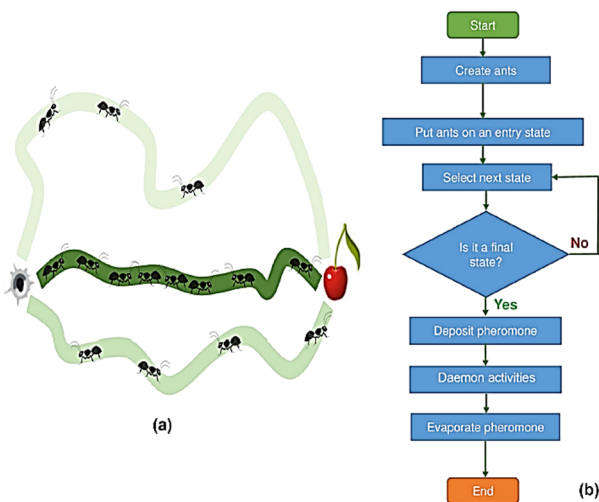
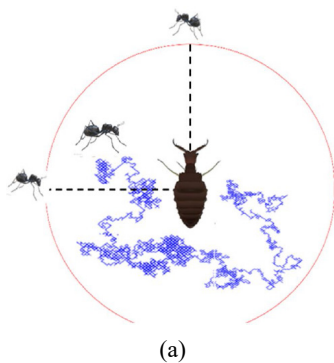
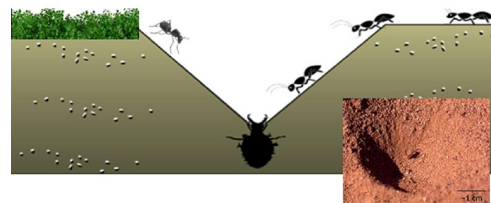


Fig. 10 Paths and pheromone of ants and their flowchart. (a) Paths of ants and the amount of corresponding pheromone; (b) Flowchart of the ants for optimization



(a)



(b)

Fig. 11 (a) Random walk in the case of the prey in the trap; and (b) the antlions hunting conduct

should be stochastically defined in the existing search space. It includes six main stages for each model repetition, as follows:

- (1) Accidental walk of prey,
- (2) Trapping in holes,
- (3) Creating a trap,
- (4) The sliding of the prey to the ant lion,
- (5) Taking the prey or creating the hole, and
- (6) Identifying the elite ant lion.

Fig. 11 shows the first stage and the antlions' hunting performance. The prey fitness assisted the ant lions' hunting ability since each hunter can hunt only one prey in this method. Therefore, a function called roulette wheel selection (RWS) is used. Further details on the ALO and the mathematical optimization procedure have been provided in the literature (Mirjalili *et al.* 2017, Kose 2018).

4. Results and discussion

As previously stated, four metaheuristic optimization methods of neural intelligence are outlined in this paper for the landslide susceptibility problem. They include the ABC, WOA, ALO, and ACO synthesized with an MLP neural network to enhance their estimation ability. The optimized values of the weights and MLP biases are contained in the solutions proposed by these algorithms. Hence, it should be introduced mathematically to the algorithms. The programming language of MATLAB 2014 was used for this purpose. The presented ABC-MLP, WOA-MLP, ALO-MLP, and ACO-MLP networks were run with the population sizes of 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 repetitions. Moreover, at the end of each iteration, RMSE and R^2 Eqs. (9) and (10) were represented to measure the performance error. The 30 and 70% values were randomly selected to select testing and training databases.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N [(Y_{i_{observed}} - Y_{i_{predicted}})^2]} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^N (Y_{i_{predicted}} - Y_{i_{observed}})^2}{\sum_{i=1}^N (Y_{i_{observed}} - \bar{Y}_{i_{observed}})^2} \quad (10)$$

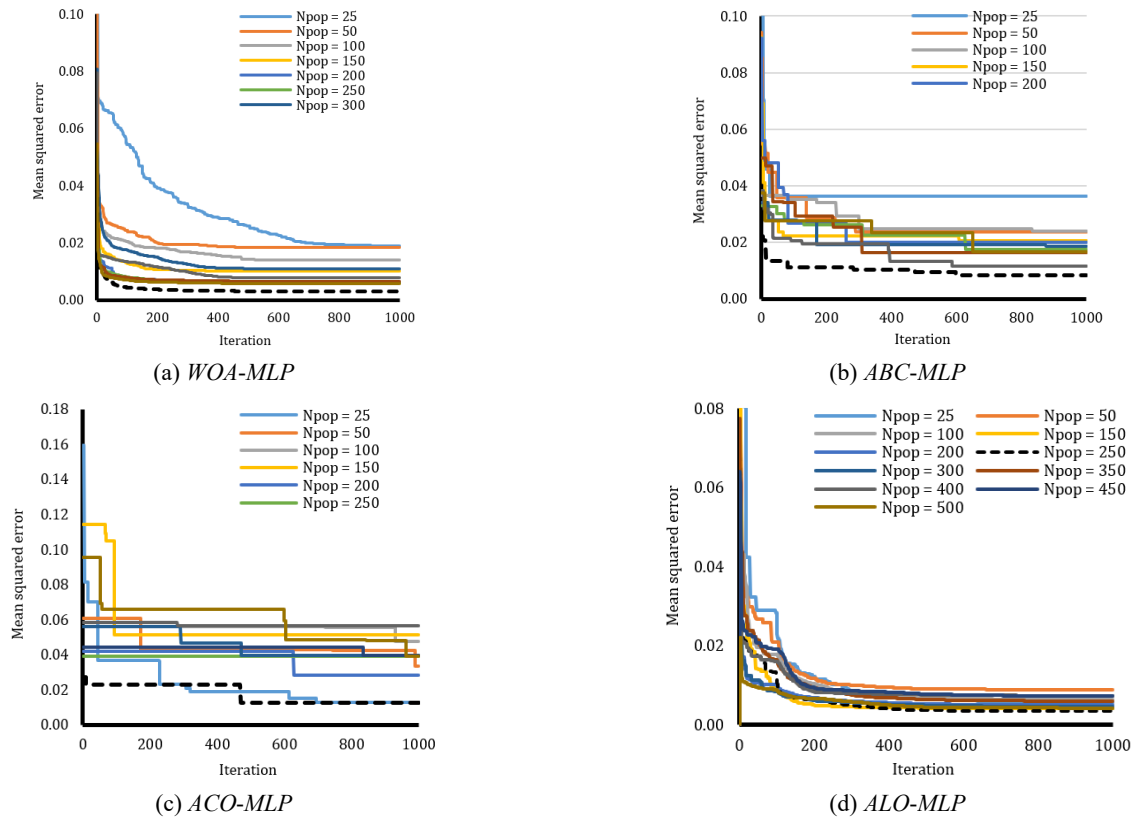


Fig. 12 Selection of best population size using the mean squared error

The best outcomes were presented by the WOA method in both testing and training ranking. Moreover, at the end of the procedure, the value of cap R squared in WOA-MLP was 0.942 and 0.987 for testing and training. Besides, the values of 0.061 and 0.064 were obtained for training and testing for RMSE. The total WOA-ANN model's ranking was 15, which was more significant than other predictive models (Table 5).

4.1 The hybrid model predicting friction capacity

As previously stated, data was estimated using four artificial intelligence approaches: ABC, WOA, ALO, and ACO. Four inputs were included in each network: the pile length (L) (m), pile diameter (D) (cm), the effective vertical stress (Sv) (kPa), and undrained shear strength (Su) (kPa). The friction capacity of the driven pile (fs) is the output and the estimation target. Hence, this section deals with the effect of the primary factors, such as pile diameter, pile length, effective vertical stress, and undrained soil cohesion, to correctly predict the friction capacity based on the design of driven piles. The parametric study was performed using the lowest-RMSE method. Driven-pile design charts were obtained based on an analysis of the outcomes. Table 6 shows the testing and training data from ABC, WOA, ALO, and ACO.

Moreover, this table compares WOA, ABC, ACO, and ALO model results with the in situ results. It was found that the RMSE value for the WOA and ALO models was lower compared to the ACO and ABC models (Fig. 12). Thus, a better convergence was found over the test data. The results

of the ALO model are similar to the WOA model based on the RMSE value. It should be noted the slight changes in the obtained RMSE represent the sufficient generality of the created models.

4.2 Model development finding

The regression plots are also presented for testing and training data sets to assess the suggested ABC, WOA, ALO, ACO, and models (Fig. 13). The findings demonstrate better accuracy and convergence for the WOA model than the ACO, ABC, and ALO models. Following the WOA model, the ACO model is ranked second based on accuracy. Besides, a slightly higher regression coefficient (R^2) was obtained for the WOA compared to the training data set's ACO, ABC, and ALO models. Thus, it can be concluded that the regression results corroborate the R^2 results.

The results for the WOA model represented better accuracy ($R^2 = 0.9315$ and 0.9611 for testing and training, respectively) compared to the other models. However, this consequence is achieved from the training data set (Table 1). If it is proved that the suggested model is reliable for the testing data, it is adequately accurate and reliable for calculating friction capacity in engineering applications. Indeed, the fabricated models need to be assessed for generality. Consequently, some data sets must be reserved for testing the validation and generality of the models, as discussed in the following lines. Finally, Fig. 14 shows the time calculation for all four models using the mean squared error.

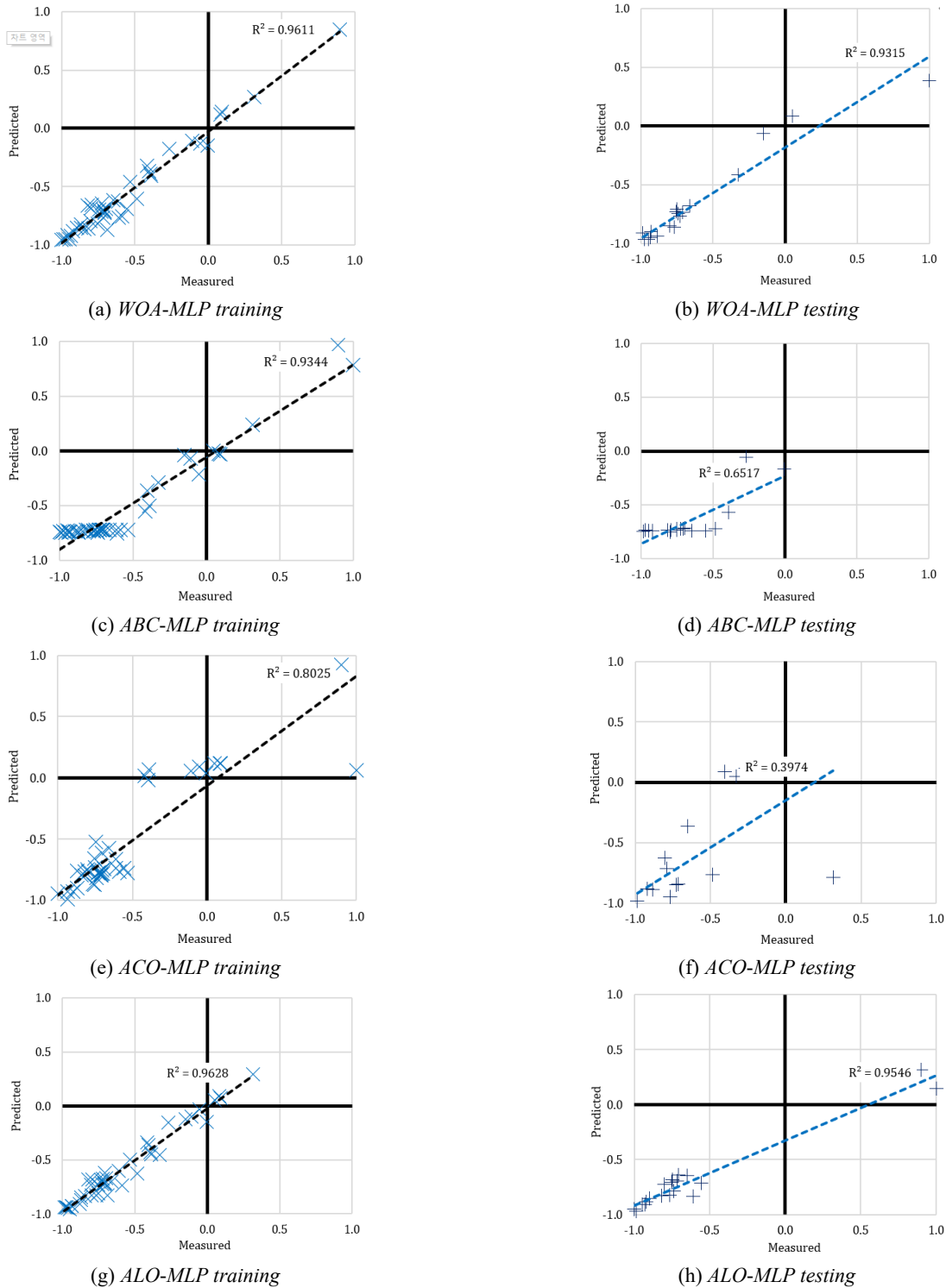


Fig. 13 Calculation time by using the R^2

As represented in Table 1, the training network accuracies were directly changed with the changes in the population size suggested in the algorithms. For example, the population size was 25, 50, 100, 150, 200, 250, 300, 350, 400, 450, and 500 in the WOA-MLP technique. The training R^2 was 0.945, 0.950, 0.063, 0.951, 0.983, 0.977, 0.971, 0.979, 0.975, 0.989, and 0.980 respectively. Similarly, R^2 was obtained at 0.943, 0.892, 0.960, 0.943, 0.934, 0.933, 0.974, 0.968, 0.962, 0.908, and 0.965 for the

same population size and hybrid technique testing (Table 2).

Also, for the same population size and ABC-MLP technique, the training R^2 was 0.903, 0.903, 0.940, 0.945, 0.952, 0.958, 0.950, 0.958, 0.964, 0.955, and 0.967, respectively. Likewise, R^2 was 0.857, 0.883, 0.832, 0.875, 0.878, 0.921, 0.885, 0.905, 0.903, 0.791, and 0.807 for the same hybrid method and population size in testing (Table 3).

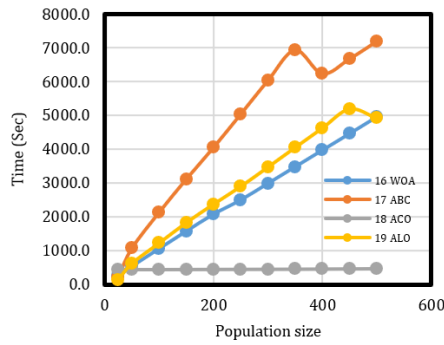


Fig. 14 Calculation time for the WOA-MLP, ABC-MLP, ACO-MLP, and ALO-MLP using the mean squared error

Table 4 shows training and testing error data for the ACO-MLP technique for the considered population size. According to the results, the quantity of R^2 was 0.883, 0.825, 0.881, 0.851, 0.636, 0.966, 0.806, 0.921, 0.852, 0.815, and 0.930 for testing and 0.962, 0.905, 0.883, 0.886, 0.891, 0.904, 0.899, 0.937, 0.856, 0.873, and 0.896 for training technique.

Error data for the ALO-MLP technique for all 11 population sizes are presented in Table 5. In this method, the quantity of R^2 is 0.951, 0.956, 0.970, 0.968, 0.955, 0.928, 0.834, 0.959, 0.984, 0.964, and 0.977 for testing and 0.982, 0.987, 0.983, 0.989, 0.982, 0.992, 0.985, 0.984, 0.978, 0.982, and 0.981 for training technique.

This study presented four hybrid evolutionary models to predict pile-bearing capacity and evaluated them based on their accuracy in training and testing datasets. Among the results, WOA stood out with the best performance, achieving an R^2 of 0.979 for training and 0.968 for testing and a low RMSE of 0.079 in training and 0.11 in testing. ALO also performed well, with an R^2 of 0.989 in training and 0.968 in testing, though it had a higher RMSE of 0.235. ABC and ACO, with R^2 values of 0.958 and 0.962 in training and 0.905 and 0.883 in testing, displayed moderate accuracy and slightly higher RMSE. In terms of ranking, WOA achieved the highest score due to its consistent performance across all metrics, followed by ALO. ABC and ACO models shared a similar total rank. The key finding is that WOA is the most reliable pile-bearing capacity estimation model. Future research should explore the refinement of these models with larger datasets and more

Table 2 Network results for the WOA-MLP based on the Shift in the size of the population

Swarm size	Training dataset		Testing dataset		Scoring				Total score	Rank
	R2	RMSE	R2	RMSE	Training	Testing				
25	0.945	0.135	0.943	0.202	1	1	5	2	9	11
50	0.950	0.133	0.892	0.143	2	2	1	6	11	10
100	0.963	0.116	0.960	0.122	4	3	7	7	21	8
150	0.951	0.098	0.943	0.220	3	5	6	1	15	9
200	0.983	0.078	0.934	0.152	10	8	4	4	26	6
250	0.977	0.076	0.933	0.182	7	9	3	3	22	7
300	0.971	0.102	0.974	0.114	5	4	11	9	29	4
350	0.979	0.079	0.968	0.110	8	7	10	10	35	1
400	0.975	0.086	0.962	0.117	6	6	8	8	28	5
450	0.989	0.054	0.908	0.074	11	11	2	11	35	1
500	0.980	0.074	0.965	0.146	9	10	9	5	33	3

Table 3 Network results for the ABC-MLP based on the Shift in the size of the population

Swarm size	Training dataset		Testing dataset		Scoring				Total score	Rank
	R2	RMSE	R2	RMSE	Training	Testing				
25	0.903	0.187	0.857	0.234	1	1	4	2	8	11
50	0.903	0.150	0.883	0.690	2	3	7	1	13	10
100	0.940	0.151	0.832	0.178	3	2	3	8	16	8
150	0.945	0.140	0.875	0.231	4	4	5	3	16	8
200	0.952	0.138	0.878	0.153	6	5	6	9	26	6
250	0.958	0.130	0.921	0.191	8	7	11	5	31	3
300	0.950	0.134	0.885	0.188	5	6	8	6	25	7
350	0.958	0.125	0.905	0.187	9	9	10	7	35	1
400	0.964	0.106	0.903	0.227	10	10	9	4	33	2
450	0.955	0.090	0.791	0.126	7	11	1	11	30	5
500	0.967	0.126	0.807	0.142	11	8	2	10	31	3

Table 4 Network results for the ACO-MLP based on the Shift in the size of the population

Swarm size	Training dataset		Testing dataset		Scoring				Total score	Rank
	R2	RMSE	R2	RMSE	Training		Testing			
25	0.962	0.111	0.883	0.218	11	10	9	7	37	1
50	0.905	0.179	0.825	0.273	9	8	5	4	26	4
100	0.883	0.214	0.881	0.124	3	3	8	11	25	5
150	0.886	0.222	0.851	0.252	4	2	6	6	18	8
200	0.891	0.165	0.636	0.389	5	9	2	1	17	9
250	0.904	0.194	0.966	0.182	8	7	11	9	35	3
300	0.899	0.194	0.806	0.320	7	4	3	3	17	9
350	0.937	0.110	0.921	0.252	10	11	10	5	36	2
400	0.856	0.233	0.852	0.138	1	1	7	10	19	6
450	0.873	0.194	0.815	0.194	2	5	4	8	19	6
500	0.896	0.194	0.630	0.325	6	6	1	2	15	11

Table 5 Network results for the ACO-MLP based on the Shift in the size of the population

Swarm size	Training dataset		Testing dataset		Scoring				Total score	Rank
	R2	RMSE	R2	RMSE	Training		Testing			
25	0.982	0.074	0.951	0.167	5	6	3	4	18	10
50	0.978	0.092	0.956	0.076	1	1	5	9	16	11
100	0.983	0.078	0.970	0.088	7	4	9	8	28	3
150	0.989	0.062	0.968	0.235	10	10	8	3	31	1
200	0.982	0.069	0.955	0.144	6	7	4	5	22	8
250	0.992	0.058	0.928	0.123	11	11	2	6	30	2
300	0.985	0.066	0.834	0.260	9	8	1	1	19	9
350	0.984	0.076	0.959	0.099	8	5	6	7	26	4
400	0.978	0.084	0.984	0.070	2	2	11	10	25	5
450	0.982	0.083	0.964	0.064	4	3	7	11	25	5
500	0.981	0.064	0.977	0.242	3	9	10	2	24	7

Table 6 Results of R² and R2 for various proposed hybrid techniques based on model population size

Method	Population size	Network result				Scoring				Total rank	RANK
		Train		Test		Train		Test			
		R2	RMSE	R2	RMSE	R2	RMSE	R2	RMSE		
WOA	350	0.979	0.079	0.968	0.11	3	3	3	4	13	1
ABC	350	0.958	0.125	0.905	0.187	1	1	2	3	7	3
ACO	25	0.962	0.111	0.883	0.218	2	2	1	2	7	3
ALO	150	0.989	0.062	0.968	0.235	4	4	3	1	12	2

diverse geotechnical conditions to improve prediction accuracy further.

5. Conclusions

This study presented four hybrid evolutionary models to predict pile-bearing capacity and evaluated them based on their accuracy in training and testing datasets. Among the results, WOA stood out with the best performance,

achieving an R² of 0.979 for training and 0.968 for testing and a low RMSE of 0.079 in training and 0.11 in testing. ALO also performed well, with an R² of 0.989 in training and 0.968 in testing, though it had a higher RMSE of 0.235. ABC and ACO, with R² values of 0.958 and 0.962 in training and 0.905 and 0.883 in testing, displayed moderate accuracy and slightly higher RMSE. In terms of ranking, WOA achieved the highest score due to its consistent performance across all metrics, followed by ALO. ABC and ACO models shared a similar total rank. The key finding is

that WOA is the most reliable pile-bearing capacity estimation model. Future research should explore the refinement of these models with larger datasets and more diverse geotechnical conditions to improve prediction accuracy further.

Acknowledgments

PhD research startup foundation of Yuncheng University (YQ-2020023); Doctor returned to Shanxi Province Project (QZX -2021006).

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