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Prediction of the Lateral Bearing Capacity of Short Piles in Clayey Soils Using Imperialist Competitive Algorithm-Based Artificial Neural Networks

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***Abstract*—**Prediction of the ultimate bearing capacity of piles (Qu) is one of the basic issues in geotechnical engineering. So far, several methods have been used to estimate Qu, including the recently developed artificial intelligence methods. In recent years, optimization algorithms have been used to minimize artificial network errors, such as colony algorithms, genetic algorithms, imperialist competitive algorithms, and so on. In the present research, artificial neural networks based on colonial competition algorithm (ANN-ICA) were used, and their results were compared with other methods. The results of laboratory tests of short piles in clayey soils with parameters such as pile diameter, pile buried length, eccentricity of load and undrained shear resistance of soil were used for modeling and evaluation. The results showed that ICA-based artificial neural networks predicted lateral bearing capacity of short piles with a correlation coefficient of 0.9865 for training data and 0.975 for test data. Furthermore, the results of the model indicated the superiority of ICA-based artificial neural networks compared to back-propagation artificial neural networks as well as the Broms and Hansen methods.

***Keywords*—**Lateral bearing capacity, short pile, clayey soil, artificial neural network, Imperialist competition algorithm.

I. Introduction

THE prediction of piles bearing capacity under lateral loading is one of the issues which is important in geotechnical engineering problems. Accurate estimation of the bearing capacity of piles is difficult due to the fact that determining the effective parameters on the piles bearing capacity is difficult and sometimes impossible. These factors can consist of physical and mechanical properties of the soil, as well as the variety of piles in terms of material features, cross-sectional shape, and pile installation methods, which illustrate a wide range of effective variables on the piles behavior [1]. So far, different methods have been proposed to estimate piles bearing capacity, and the most common one is the Broms method [2]. In addition to Broms, other researchers have done some studies in this field [3]-[6].

In recent years, soft computational methods for modeling complex problems in geotechnical engineering have been widespread [1]. These methods include artificial neural networks, support vector machines, and so on [7]. The advantage of these methods is that the pattern of the phenomenon is directly learned from empirical and experimental results, and the errors in the empirical and experimental data do not have much effect on the network.

Baranti et al. examined the bearing capacity of displacement piles in sandy soils using artificial neural networks. The results showed that multilayer artificial neural networks could predict the bearing capacity of piles in sandy soils well [8]. In addition, Das and Basudhar studied bearing capacity of piles using artificial neural networks. Their results showed that artificial neural networks provide better estimates of the lateral bearing capacity of the piles rather than experimental methods [9]. Kordjezi et al. examined the vertical loading capacity of the piles using a support vector machine (SVM). They found that SVMs were able to estimate the vertical bearing capacity of the piles with higher accuracy Compared with artificial neural networks [10]. Furthermore, Samui [11], Zhang et al. [12], Liu et al. [13] examined the frictional load bearing capacity of piles and the axial load bearing capacity of piles with the help of SVM.

In recent years, optimization algorithms have been used to minimize neural network errors, which these algorithms include the Genetic Algorithm (GA) and the Imperialist Competitive Algorithm (ICA). Ardalan et al. examined the prediction of bearing capacity of piles using polynomial neural networks and GA. They found that the GA was able to reduce the neural network error [14]. Moreover, Momeni et al. investigated the prediction of bearing capacity of piles using GA based artificial neural networks. Their results illustrated that artificial neural networks based on the GA perform better than conventional artificial neural networks in estimating the bearing capacity of the piles [15]. Over the last few decades, various researchers have predicted the bearing capacity of the piles using soft computing methods [16]-[18].

According to previous studies, various methods have been used to estimate piles bearing capacity. But so far, Imperialist Competitive Algorithm has not been used to minimize the error of the presented model. In the present research, an artificial neural network based on the Imperialist Competitive Algorithm is used to predict the lateral bearing capacity of short piles.

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II. Multi-Layer Perceptron Artificial Neural Networks

An artificial neural network is a collection of simple, interconnected computing elements called the neuron, whose learning ability allows the system to learn complex relationships. These computing units are related to a large number of interconnections, in which all of the knowledge gained from the environment is stored in it. Fig. 1 shows the mathematical model of a neural neuron.

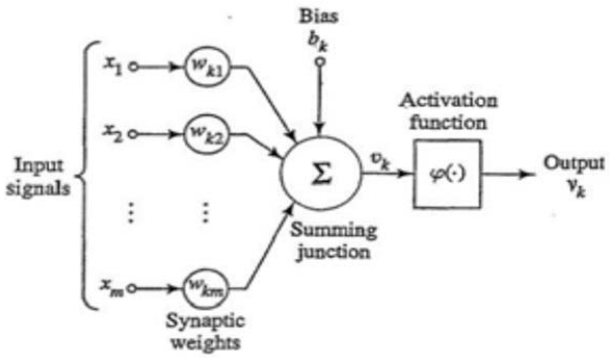


Fig. 1 Neural neuron mathematical model [8]

Neural neurons include a set of connections that are characterized by weight or resistance values. A signal, connected to the neuron, is multiplied by weight. A collector collects inputs into the neuron with a bias value. Also, an activity function is used to limit the output of a neuron in a desirable range.

One of the most commonly used neural networks is the multilayer perceptron network, or MLP network. This network has one input layer, one output layer, and some hidden layers. In this network, each neuron in each layer is connected with all the neurons of the preceding and the next layer, which has no backward connections in the network. MLP networks with a hidden layer with differentiable transfer functions in the middle and exit layers can approximate all functions with any degree of approximation, provided that they have enough hidden layer of the neuron [8]. Fig. 2 shows the model of a multi-layer nerve network.

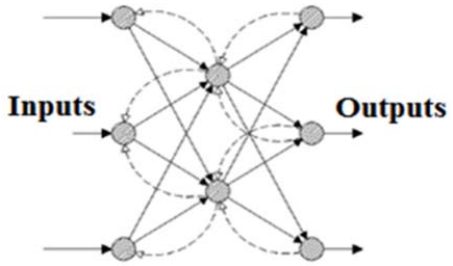


Fig. 2 Architecture of a multi-layer neural network [19]

The number of neurons in hidden layer has a great influence on the behavior of the network. If the number of neurons is low, the network cannot accurately reflect the nonlinear mapping between the input and the output. On the other hand, if the hidden layer of the neuron is more than enough, the network will maintain the training data by producing a nonlinear complicated data map. But in contrast to the new data, it does not perform well, and in fact, the network loses its generalization power. The number of hidden neurons is empirically obtained [20]. Back-propagation algorithm (BP) is one of the most popular and most effective algorithms for training MLP networks [21].

By using the BP algorithm, the output error of the problem is reduced by adjusting the weight of the connections. At the beginning, the network is trained with randomly selected weights. Then, using the feed-forward back propagation algorithm, all signals are displaced between the output and the middle layers. At the end, the output of the problem is calculated using the network and the difference between the target output and the predicted output is calculated. The difference between these two outputs is the network error. Then, the network weights are corrected. This process continues to reach the lowest error [22], [23].

III. Imperialist Competitive Algorithm

In 2007, Atashpaz and Lucas presented the Imperialist Competition Algorithm inspired by the colonial phenomenon [24]. The solution of the optimization problem in this way is through the simulation of the socio-political process of colonialism.

In this way, the initial population of probable answers is called the "country". To get the least error (lowest cost), countries with the best colonial position are called imperialist countries. Imperialists pull some of the colonies based on their power and form the "empires". After the formation of the empire, the colonies begin to move toward the corresponding imperialists. In an N-dimensional optimization problem with the help of the ICA, each country is defined as an array of 1 × N as follows:

$$Country = (P_1, P_2, P_3,\ldots,P_{Nvariable})$$

in which Pi is the parameter that needs to be optimized. Each parameter is defined in a country as a political-social characteristic. The ICA is trying to determine the countries with the best political-social combination. This process can lead to finding the best solution to the problem. To continue this process, the cost function is defined as follows:

$$Cost=f(country)=f(P_1, P_2, P_3,\ldots,P_{Nvariable})$$

The process of optimization starts with the selection of the strongest nations as imperialist (N_{imp}). The rest of the nations are then known as the colony (N_{col}). Each of these colonies is a member of an empire. The normalized cost of each imperialist is determined as follows:

$$C_n = c_n - max_i\{c_i\} \quad (1)$$

where c_n is the nth colonial cost, and C_n is the normalized cost. Similarly, the normalized power of each imperialist is defined

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using the normalization of all imperialists:

$$p_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} C_i} \right| \quad (2)$$

Then, the number of initial colony in each empire is as:

$$NC_n = round\{p_n . N_{col}\} \quad (3)$$

where N_{Cn} is the initial number of colonies for the nth empire and N_{col} is the total number of colonies. The next stage is the integration phase in which imperialists are trying to attract colonies. Fig. 3 illustrates the process of moving the colonies toward the imperialist. The parameter x is determined as follows:

$$x \sim U(0, \beta \times d) \quad (4)$$

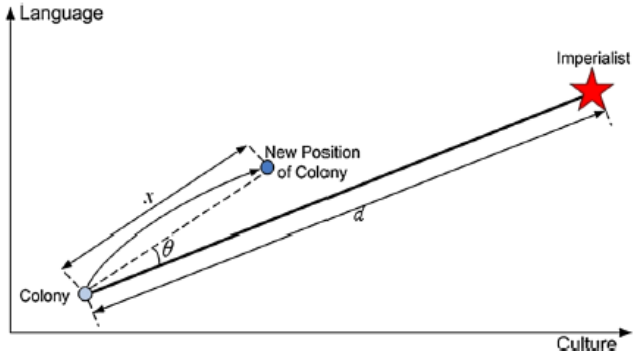


Fig. 3 Moving the colony towards the corresponding imperialist [24]

where β is a number larger than 1, and d is the distance between colony and imperialist. The colonial movement is not always a direct vector. To increase the search capability around imperialist, as shown in Fig. 4, a deviation value (parameter θ) is added randomly to the direction of the movement.

$$\theta \sim U(-\gamma, \gamma) \quad (5)$$

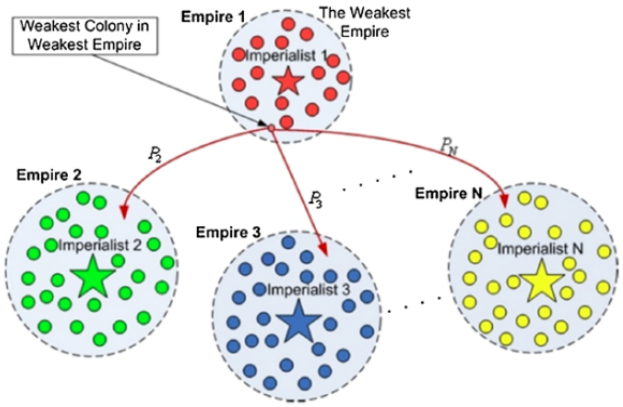


Fig. 4 Searching for more powerful imperialist [24]

where γ is a variation to adjust the deviation. β and γ are arbitrary values, but the values of 2 for β and π/4 rad for γ converge to a general minimum [24]. In the next step, a revolution will occur, resulting in a sudden change in the characteristics of the colonies. This will be done to increase the ability to search and prevent falling into local minimum. Consequently, the colony with the lowest cost changes its position to the imperialist, and the algorithm continues with the imperialist in the new position. The total power of the empire is as follows:

$$TC_n = Cost(imperialist_n) + \xi mean\{Cost(colonies\ of\ empire_n)\} \quad (6)$$

where T_{Cn} is the total cost of the nth empire, and ξ is a small positive number. When ξ is a small number, the power of a whole empire is only affected by imperialist power. As the value of ξ increases, the role of the colonies increases in the power of the whole empire. However, the number of 0.1 for ξ in most cases has good results [24].

The final stage is the process of optimizing imperialist competition. At this stage, all imperialists try to control the colonies of other empires. Hence, the power of the strongest empire increases, and the power of the weakest empire decreases gradually. Moreover, this process will help to converge to a minimum, providing that it continues. The optimization process is then stopped using an endpoint algorithm. The ICA flowchart is shown in Fig. 5.

IV. Design of the Model

A. Database

In order to achieve an efficient model for predicting piles bearing capacity, there is a need for information about the pile and the surrounding soil.

In this study, the data published by Rao and Suresh Kumar were used [25]. These data include the pile diameter (D), the embedded length of the pile (L), the eccentricity of load (e), and the soil undrained shear strength (Su). These data include 38 small scale piles loading tests under lateral load in clayey soils. All the piles were short and rigid. In 2006, Das and Basudhar used the same data to estimate piles bearing capacity by artificial neural networks [9]. In addition, they compared the results with the Broms and Hansen methods [9]. The results indicated that the artificial neural networks method is superior in predicting the bearing capacity of the piles [9]. In the present study, 80% of the data were allocated to the training and the rest of the data was devoted to the evaluating [9]. Table I shows the statistical characteristics of the input and output data of the model.

Data were transmitted to the range [-1, 1] due to the fact that input and output data of the problem consist of a wide range. This action has an effect on the convergence and proper performance of the network [26]. Hence, in the present research, the following linear transformation was used to transfer data to the desired range:

$$NP = \frac{UB-LB}{MaxP-MinP} \times (SP - MinP) + LB \quad (7)$$

in which UB and LB are the upper and lower bounds of the range, MinP and MaxP are the minimum and maximum value of data, and SP and NP are the values of real and normalized data.

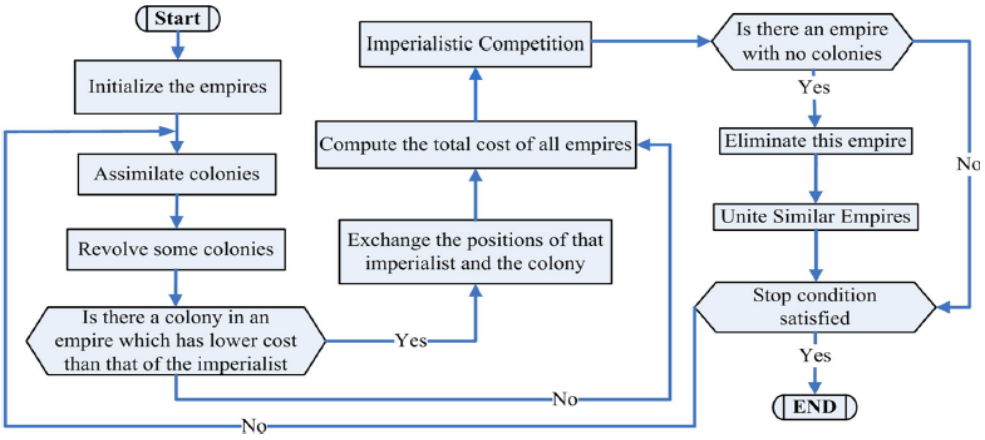


Fig. 5 Flowchart of imperialist competition algorithm [30]

TABLE I
STATISTICAL DATA OF INPUT AND OUTPUT DATA MODEL [25]

Statistical characteristics	Pile diameter (mm)	Pile length (mm)	Eccentricity of load (mm)	Undrained shear strength of soil (kPa)	Pile bearing capacity (N)
Max	33.3	300	50	38.8	225
Min	6.35	130	0	3.4	29.5
Mean	17.78	278.89	44.17	9.94	73.69
STD	6.12	52.82	14.73	10.11	38.36

B. Model Performance Evaluation Indicators

In order to evaluate the accuracy of the model obtained from the neural network, statistical indices such as coefficient of correlation (CC), mean square error (MSE), root mean square error (RMSE) and mean absolute error (MAE) were used. The values of the mentioned indices are obtained using the following relationships:

$$CC = \frac{\sum_{i=1}^{n}[(s_i-\bar{s}_i)(c_i-\bar{c}_i)]}{\sqrt{\sum_{i=1}^{n}(s_i-\bar{s}_i)^2(c_i-\bar{c}_i)^2}} \quad (8)$$

$$MSE = \frac{\sum_{i=1}^{n} E_i^2}{n} \quad (9)$$

$$RMSE = (MSE)^{0.5} \quad (10)$$

$$MAE = \frac{\sum_{i=1}^{n}|E_i|}{n} \quad (11)$$

$$E_i = (s_i - c_i) \quad (12)$$

In these equations, ci is the mean of the observed values of the variable, si is the mean of the calculated model, ci is the actual observational value of the variable, si is the calculated value of the variable by the model and n the number of observational data.

C. Model Used

Various methods have been used for training neural networks such as GA, particle swarm algorithm, ant colony algorithm, and so on. The purpose of these algorithms is to obtain the weights and the constant value, in such a way that the network error is minimized. In this paper, an imperialist competitive algorithm was used for network training.

Achieving the best answer depends on the number of countries and the number of imperialist countries. Twelve different states of the total number of countries and imperialist countries were studied. According to Table II, the case with the total number of countries of 80 and the number of imperialist countries of 5 had the best performance.

TABLE II
BEST IMPERIALIST COST FOR DIFFERENT MODELS

Model number	Number of countries	Number of imperialists	Best cost of imperialists
1	20	2	0.0071
2	40	3	0.0337
3	60	4	0.0095
4	80	5	0.0047
5	100	6	0.0091
6	120	7	0.0089
7	140	8	0.0145
8	160	9	0.0084
9	180	10	0.0081
10	200	11	0.0094
11	220	12	0.0069
12	240	13	0.0279

To get an efficient model, network architecture has a great impact on network performance. The ICA is only able to adjust the weights and the constant value (bias) of the network and minimize the network error. A network with a hidden layer is able to estimate any continuous functions [27]. In this research, a network with two hidden layers was used. The number of neurons in each layer is the most fundamental characteristic of network architecture [28], [29]. There is no definite rule for determining the number of neurons in a layer. In the work of various researchers, a number is proposed between 1 and 18 neurons per layer [28], [29]. In this study, using a trial-error method, a number of networks with a hidden

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layer and with a different number of neurons were trained and tested. 80% of the data were used for training and the remaining 20% were used for testing. The analysis was done in two ways, ANN-BP and ANN-ICA, and these two methods were compared with each other. According to Figs. 6 and 7, neural network error based on the imperialist competitive algorithm was less than the error of neural network based on the back-propagation algorithm as it can be seen in all cases. Also, 16 neurons for layers were selected as the optimal number.

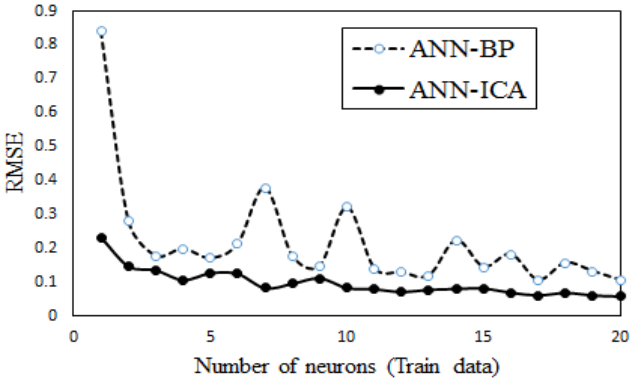


Fig. 6 Neural network error for different number of neurons (training data)

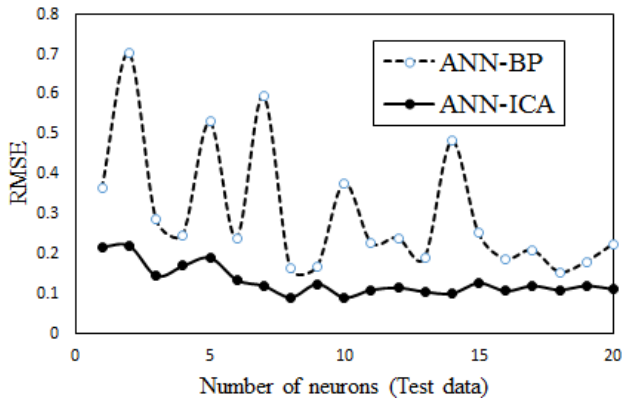


Fig. 7 Neural network error for different number of neurons (test data)

V. Model Results

In Figs. 8 and 9, the results of training and testing data for ANN-BP and ANN-ICA networks are presented. With regards to the correlation between the results of the experiments and the developed models, it can be concluded that the artificial neural networks based on the imperialist competitive algorithm, are more capable of learning the governing pattern of the piles bearing capacity inasmuch as they are not trapped in the local extremes. Also, Table III illustrates the performance of the ANN-ICA model. According to the obtained results, the model presented by the proposed model is highly accurate. Figs. 10 and 11 also show that the predicted output is closely related to the output observed from the experiment.

According to the results, the correlation coefficient for training data is 0.9865 and for the testing data is 0.9715.

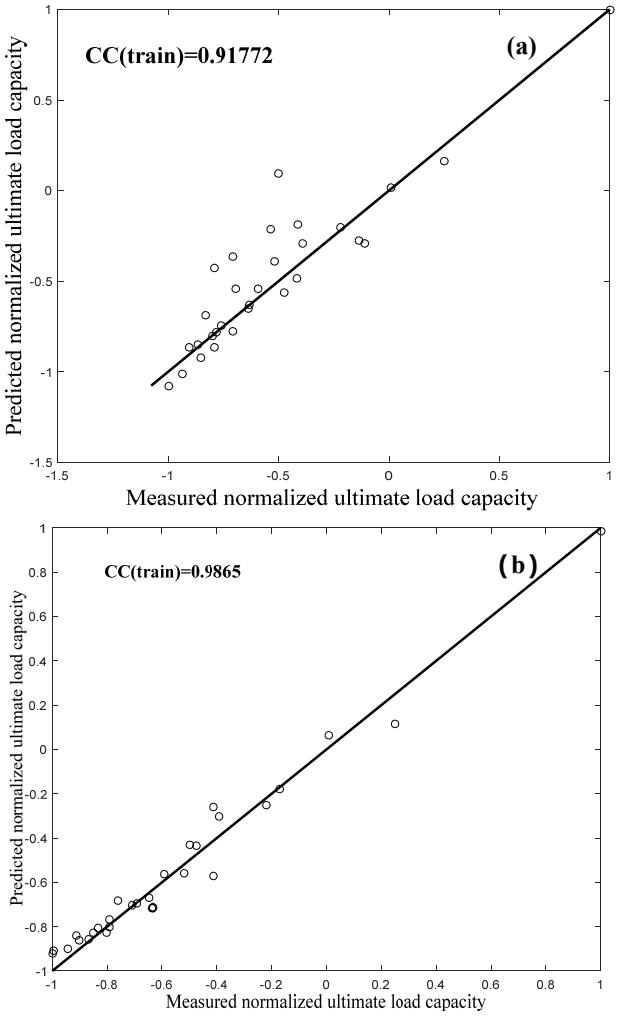
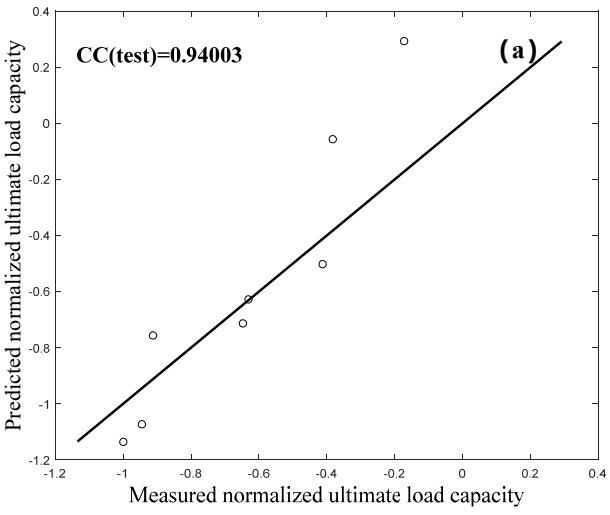


Fig. 8 Correlation between measured and predicted results for training data (a) ANN-BP (b) ANN-ICA



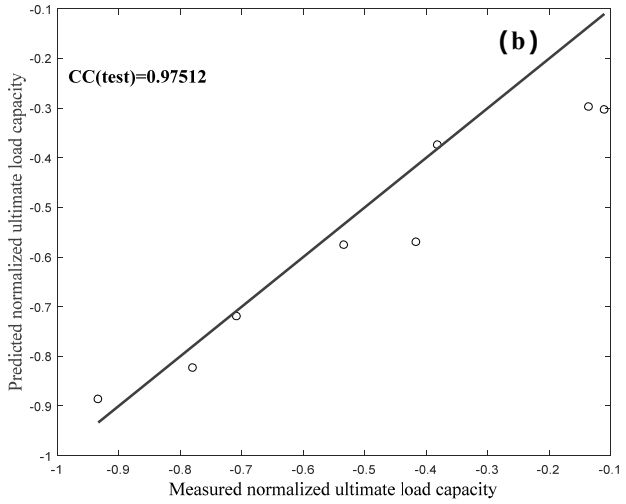


Fig. 9 Correlation between measured and predicted results for testing data (a) ANN-BP (b) ANN-ICA

Table IV shows the comparison between artificial neural networks based on imperialist competitive algorithm with back-propagation artificial neural networks, Broms method and Hansen method. As it is known, artificial neural networks based on the imperialist competitive algorithm, due to the fact that they are not trapped in the local extremes, have a better performance than the other methods. The results of the Broms and Hansen methods are taken from the reference number [9].

TABLE III
PERFORMANCE RESULTS OF THE ICA-BASED NEURAL NETWORK MODEL

MLP-based on ICA	CC	MSE	RMSE	MAE
Testing data	0.986	0. 0046	0.068	0.0538
Training data	0.975	0.0114	0.107	0.0816

TABLE IV
COMPARISON OF THE PERFORMANCE OF VARIOUS METHODS

Method	Data	CC
MLP-based on ICA	Training data	0.986
MLP-based on ICA	Testing data	0.975
MLP-based on BP	Training data	0.9177
MLP-based on BP	Testing data	0.94
Broms method	All data	0.967
Hansen method	All data	0.941

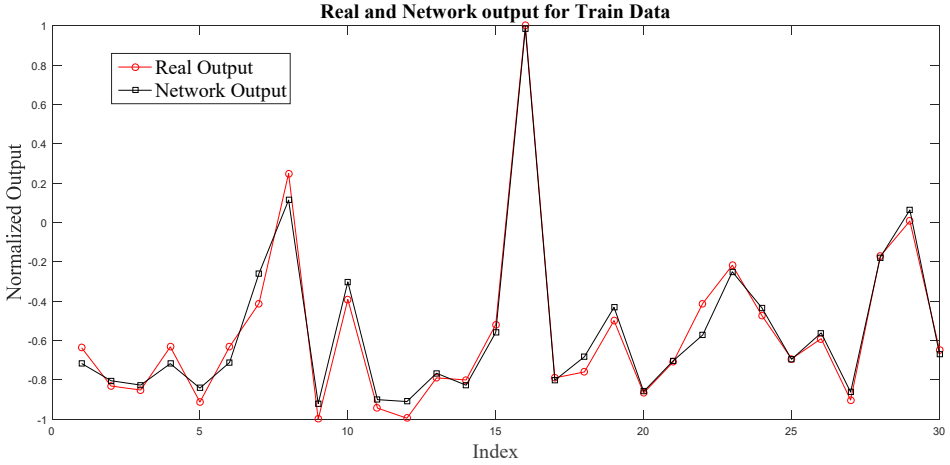


Fig. 10 The results of the model for the training data

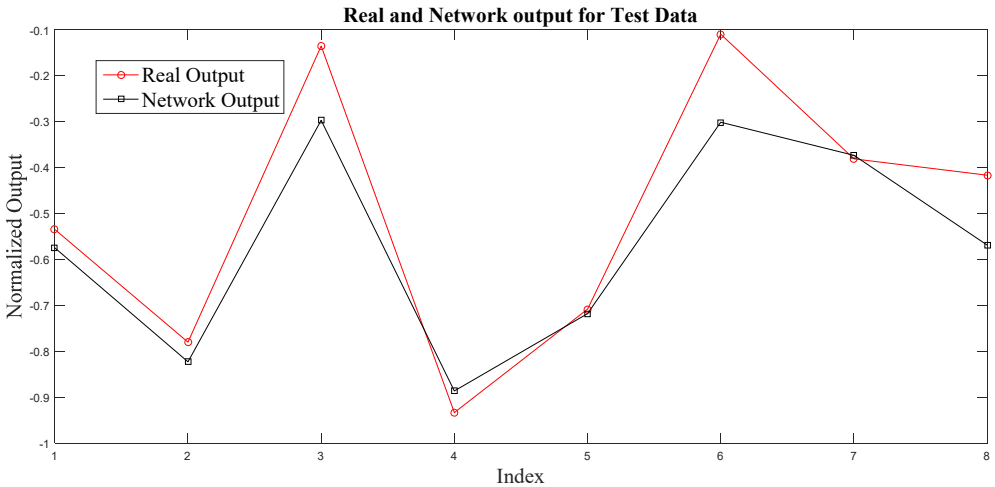


Fig. 11 The results of the model for the testing data

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For further investigation, the ratio of the predicted lateral bearing capacity to the measured load bearing capacity (Qp/Qm) against the cumulative potential (p) was also plotted. This chart is one of the probabilistic graphs that provides valuable information. In this way, the predicted lateral load bearing capacity ratio was sorted ascending and cumulative probability was obtained using (13).

$$p = \frac{i}{r+1} \tag{13}$$

in which, i is the case where the cumulative probability factor is calculated, and r is the total number of reviews.

This method offers valuable information in analyzing the dispersion of predictive methods:

1. The ratio of the predicted to the measured data at p = 50% indicates the tendency of the method to be low or high. The closer the number to one is the better.
2. The slope of the line shows the dispersion and standard deviation. If the slope of the line decreases, it will indicate better performance of the model.

Fig. 12 shows the ratio of the predicted bearing capacity to the measured load bearing capacity against the cumulative potential. As can be seen, in the p = 50% the ratio of the load bearing capacity is very close to value of 1, indicating the proper performance of the model. Also, the slope of the ANN-ICA line in relation to the ANN-BP network suggests a more accurate prediction of the model based on the imperialist competitive algorithm. In addition, at p = 90%, the relative bearing capacity of the ANN-ICA network is close to 1.17, indicating that the model is close to reality for most of the data. This value for the ANN-BP network is close to 1.42.

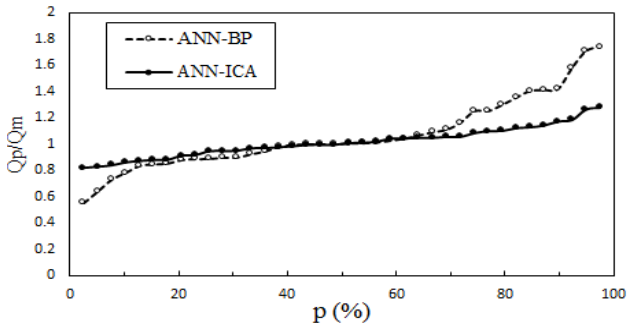


Fig. 12 The ratio of the predicted to the measured data against the cumulative potential

VI. Sensitivity Analysis

Artificial neural networks can only learn the pattern of the phenomenon through training, but they are not able to determine how different parameters influence the output. By the sensitivity analyzing, we can see the effect of each input on the output of the problem. For this purpose, by changing one of the input parameters while other parameters were kept constant, the effect of the mentioned parameter on the output was investigated. Figs. 13-16 show the effect of the pile diameter, the embedded length of the pile, the eccentricity of load, and the undrained shear strength of soil on the lateral bearing capacity of the short piles. According to these figures, increasing in the length of the pile, pile diameter, and the soil undrained shear strength as well as the reduction of the eccentricity of load lead to increase in the piles ultimate bearing capacity.

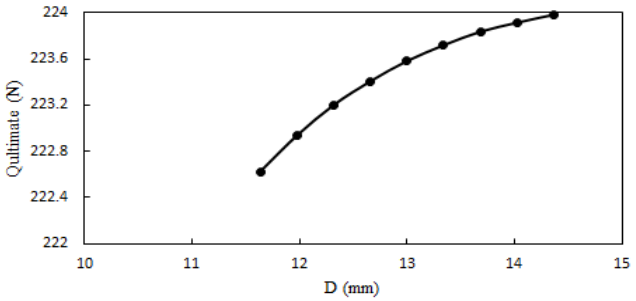


Fig. 13 Sensitivity results of the ANN-ICA model to the diameter of the piles

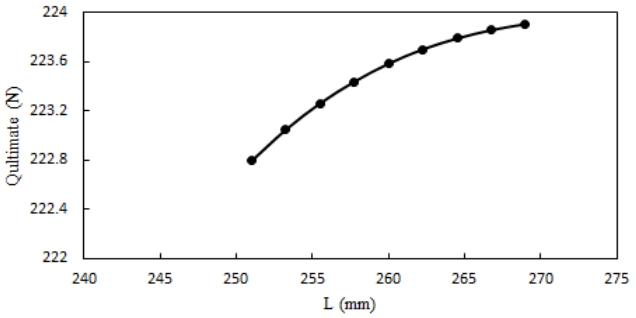


Fig. 14 Sensitivity results of the ANN-ICA model to the length of the piles

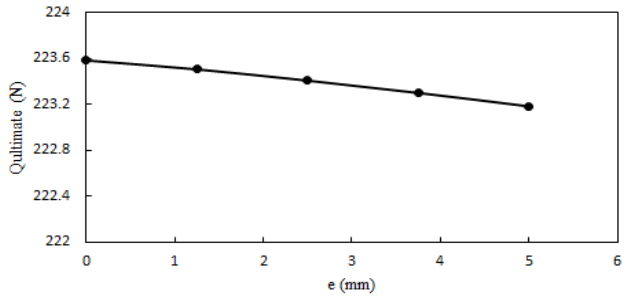


Fig. 15 The results of the ANN-ICA model's sensitivity to the eccentricity of load

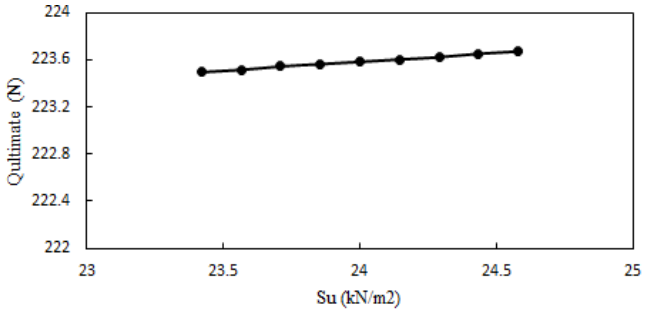


Fig. 16 Sensitivity results of ANN-ICA model to the undrained shear strength of soil

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VII. Conclusion

In the present paper, multi-layer perceptron (MLP) neural networks based on the Imperialist Competitive Algorithm (ICA) were used to predict the lateral bearing capacity of short piles in clayey soils. Data from 38 small scale tests were used to train and test the model. By comparing the results obtained from the neural network and the laboratory results, it was observed that the training data with statistical indices CC = 0.986 and RMSE = 0.06822, as well as test data with CC = 0.975 and RMSE = 0.1071 are able to predict experiment results. Also, the results of the model showed the superiority of ICA-based artificial neural networks compared to back-propagation based artificial neural networks as well as the Broms and Hansen methods. The results of the sensitivity analysis of the model showed that the pile diameter had the greatest impact and the soil undrained shear strength had the least effect on the pile ultimate lateral bearing capacity.

The scope of application of the results obtained in the present study is limited to the data used in constructing the model. Therefore, the neural network model is always able to learn new data, and it can re-train the network by entering a wider range of data.

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