Engineering with Computers (2019) 35:1463–1474
https://doi.org/10.1007/s00366-018-0674-7

ORIGINAL ARTICLE

Applying several soft computing techniques for prediction of bearing capacity of driven piles

Sadulla Shaik[1] · K. Sri Rama Krishna[2] · Mazhar Abbas[3] · Munir Ahmed[4] · Dinesh Mavaluru[5]

Received: 31 October 2018 / Accepted: 4 December 2018 / Published online: 17 December 2018

Abstract

Pile as a type of foundation is a structure which can transfer heavy structural loads into the ground. Determination and proper prediction of pile bearing capacity are considered as a very important issue in preliminary design of geotechnical structures. This study attempts to develop several intelligent techniques for prediction of pile bearing capacity in cohesionless soil. To show the effects of fuzzy inference system and imperialism competitive algorithm (ICA) on a pre-developed artificial neural network (ANN), two hybrid ANN models namely ICA-ANN and adoptive neuro-fuzzy inference system (ANFIS) were considered and developed to estimate pile bearing capacity. Then, results of these techniques were compared with those of ANN model and the best one among them was chosen according to the results of performance indices. Several parameters (i.e., internal friction angle of soil located in shaft and tip, effective vertical stress at pile toe, pile area, and pile length) were set as model inputs, while the output is the total driven pile bearing capacity. As a result of the developed models, coefficient of determination (R^2) values of (0.895, 0.905), (0.945, 0.958), and (0.967, 0.975) were obtained for training and testing data sets of ANN, ICA-ANN, and ANFIS models, respectively. The results showed that both hybrid models are able to predict bearing capacity with high degree of accuracy; however, ANFIS receives more applicable based on used performance indices and it can be utilized for further researchers and engineers in practice.

Keywords Pile bearing capacity · ANN · ICA · ANFIS · Hybrid model

1 Introduction

In general, it is too expensive and time consuming to carry out a parametric research on the response of pile (of both bored and driven types) in a static and dynamic load experiment in the field, and it might be confined by scaling impacts at the model scale [1, 2]. Furthermore, a number of field tests need to be carried out in each project. To decrease the cost of a project, it is important to reduce the number of tests needed [3–5]. Proposing some intelligent techniques, we can achieve this end. Artificial neural networks (ANN) have been applied very extensively to the solution of several complex problems; this has resulted in a great attention to these networks and their utilization in civil and geotechnical engineering [6–23]. Such popularity is because of its competency in the exploration of complex nonlinear relationships that may exist amongst various parameters.

Literature consists of many studies conducted on the use of the ANN-based models for the purpose of predicting some factors such as the pile settlements [24], the piles' lateral load capacity, the bearing capacity of pile foundation

✉ Sadulla Shaik
sadulla09@gmail.com

K. Sri Rama Krishna
kalvasrk@gmail.com

1 Department of Electronics and Communication Engineering, Vignan's Foundation for Science Technology and Research University, Vadlamudi, Guntur, Andhra Pradesh 522213, India

2 Department of Electronics and Communication Engineering, Velagapudi Ramakrishna Siddhartha Engineering College, Vijayawada, Andhra Pradesh 520007, India

3 COMSATS University Islamabad, Vehari Campus, Islamabad, Pakistan

4 COMSATS University Islamabad, Vehari Campus, Islamabad, Pakistan

5 College of Computing and Informatics, Saudi Electronic University, Riyadh, Saudi Arabia

[25], the effectiveness level of the pile groups that have been installed in regions with sandy soil [26], driven piles in soils that are not cohesive [27], the use of methods that are based on SPT to predict the toe bearing capacity of driven piles [28], and the base resistance of open-ended piles [29]. The design of driven piles in sand was studied by Randolph et al. [30] proposing a design approach that took well into consideration the impacts of confining stress on two elements of sand, i.e., its frictional characteristics and compressibility, which may result in an impact on the end-bearing capacity. At the final step, a comparison is made between the resultant design approach and the in situ data, and the impacts of the most important factors, e.g., the direction of loading, are discussed. Alawneh et al. [31] investigated the axial compressive capacity of driven pile in cohesionless sand. In this solution, post-driving residual stresses were also included. An innovative empirical formulae was applied to friction angle of the sand, average effective vertical stress, relative density, the recognized bearing capacity factor of the piles (Nq and β), as well as the deformability level of the soil when it is underneath the pile toe. A database was constructed containing a total of 28 axially compressive pile load tests. The predicted and measured compressive capacities of an independent database were compared to each other; the obtained results confirmed the accuracy and reliability of the proposed formula. Yang et al. [32] attempted to have a deep insight into how jacked and driven piles behave in sandy soils. They carried out a wide-ranging in situ study aiming at the exploration of the differences and similarities between the way the driven H-piles and jacked H-piles behave. The length of the instrumented piles was fixed between 32 and 55 m having a pile design bearing capacity of up to 3540 kN. Findings showed a correlation between the ultimate shaft friction and the value of mean standard penetration test (N). This suggested that the shaft friction capacity could be taken as 1.5 (N) over bar to 2 (N) over bar (kPa) in case of both driven and jacked H-piles. A research was conducted by Lee et al. [33] to investigate the combined load (i.e., lateral and vertical load) response of the driven pile models in sand. Numerous lateral load experiments were carried out on the pile simultaneously exposed to vertical loads. As shown by findings of combined load test, in cases where a vertical compression load (driven pile installed in sand) exists, the lateral capacity reduces. Consequently, where axial loads existed, a considerable increase (by 10, 36, and 39% for loose, medium dense, and dense sand, respectively) occurred in the bending moments at the pile head. Adopting the approach of MARS (multivariate adaptive regression spline), Samui [34] attempted to explore the ultimate capacity of the driven piles that were installed in sand. In the MARS approach, a variety of parameters are taken into account as input variables, including driven pile area (A), pile length (L), the angle of shear resistance of the soil that surrounds the shaft (φ shaft) and soil at the tip of the derived pile (φ tip), and effective vertical stress at the tip of the pile (σv). On the other hand, its output is the ultimate bearing capacity of the pile. A comparison was made between the results obtained from MARS and those of the other developed ANN-based models, e.g., GRNN (Generalized Regression Neural Network). At the final step, based on the proposed MARS, an equation was provided. The driven pile bearing capacity in clay was tested by Dzagov and Razvodovskii [35], reporting that, based on the properties of the surrounding soil and pile length, the driven piles can arrange for basic characteristics that can be recognized as both end-bearing and/or friction piles. Momeni et al. [18] made use of ANN to predict the shaft and tip resistances of concrete piles. They developed an ANN-based predictive model in a way to efficiently estimate the axial bearing capacity of the bored piles and their distribution. A total of 36 PDA (pile driving analyzer) tests were carried out on different concrete piles for the purpose of constructing the network. The researchers gathered the required data from a variety of project sites. The results obtained from PDA, soil investigation data, and pile geometrical features were applied to the process of constructing the ANN models. As confirmed by findings, ANN was able to predict the ultimate, shaft, and tip bearing resistances of the piles. The coefficients of determination (R^2) equaled 0.941, 0.936, and 0.951 for testing data. This showed that the shaft, tip, and ultimate bearing capacities of piles that were predicted by the proposed ANN-based model well conformed those of in situ pile. In addition, sensitivity analysis indicated that length and area of the piles were dominant factors in the developed predicting model.

As mentioned earlier, ANN has been developed extensively for engineering and science fields. Although ANN as a prediction model benefits from various gradient-based learning approaches, two major problems may occur during learning process, i.e., getting trapped in local optima and slow convergence rate [36–39]. One efficient way of dealing with the mentioned problems is to design hybrid systems of ANN. In this study, two hybrid models, namely, imperialism competitive algorithm (ICA)-ANN and fuzzy inference system (FIS)-ANN or adoptive neuro-fuzzy inference system (ANFIS), were selected and applied to predict bearing capacity of the driven piles. Then, performance of these hybrid models was compared to performance prediction of ANN model and the best one among them was selected. In the following, after some explanations about implemented methods and the used data sets, modeling process of the developed predictive techniques is described. Then, performance prediction of these models is evaluated and compared, and the best model is selected accordingly for prediction of bearing capacity of the driven piles.

2 Methods

2.1 Artificial neural networks

Artificial neural networks refer to methods of parallel information processing capable of expressing the complex and nonlinear relationships using the number of input–output training patterns extracted from experimental data. Using its intrinsic capability, an ANN makes available a nonlinear mapping between inputs and outputs [40]. A neural network architecture that is known as the most popular one is feed-forward neural network wherein the signals or information will be propagated in only one direction; from input towards output [41, 42]. A three-layer feed-forward neural network that is well equipped with back propagation algorithm will be capable of approximating any nonlinear continuous function to an arbitrary accuracy [43]. Training the network is done through optimizing the weights for each node interconnection and bias terms until, at the output layer neurons, the output values are close as much as possible to actual outputs. To learn more about ANN structure and implementation, some other references [44–46] can be considered.

2.2 Imperialist competitive algorithm

One of the optimization algorithms is the imperialist competitive algorithm (ICA) developed by Atashpaz-Gargari and Lucas [47]; its performance is on the basis of a global search population technique. The initial step of this algorithm comprises a number of countries as random initial population. In the initial stage of this system, a random number of countries ($N_{country}$) are created. Then, the countries with the minimum costs or lowest mean-square error (MSE) or root-mean-square error (RMSE) are selected as the imperialists (N_{imp}) (the most powerful countries), while the rest of the countries are assigned as colonies (N_{col}). After that, the colonies are distributed among the empires based on the initial power of the empires. In this system, more colonies are assigned to more powerful imperialists that actually stand for individuals with the minimum costs.

ICA, comparable to other optimization algorithms, involves three operators, i.e., assimilation, revolution, and competition. A colony may turn into imperialist through the assimilation operation. In the revolution operation, position of the countries is subjected to a number of sudden movements. Therefore, during the operations of assimilation and revolution, a colony has chance to get more stable. In the competition operation, the imperialists attempt to gain more colonies, and for all of the empires, it is attractive to take possession of other empires' colonies. Such competition will cause weaker empires to lose power and stronger empires to gain more and more power. This process goes on until all of the weak empires are totally collapsed or the predefined termination criterion (e.g., RMSE, MSE, or maximum number of decades) is met. Remember that there is a similarity between the number of decades in ICA and the number of generations in genetic algorithm (GA). The ICA algorithm and its structure are shown in Fig. 1. To gain more information about ICA, refer to related studies in the literature [14, 48, 49].

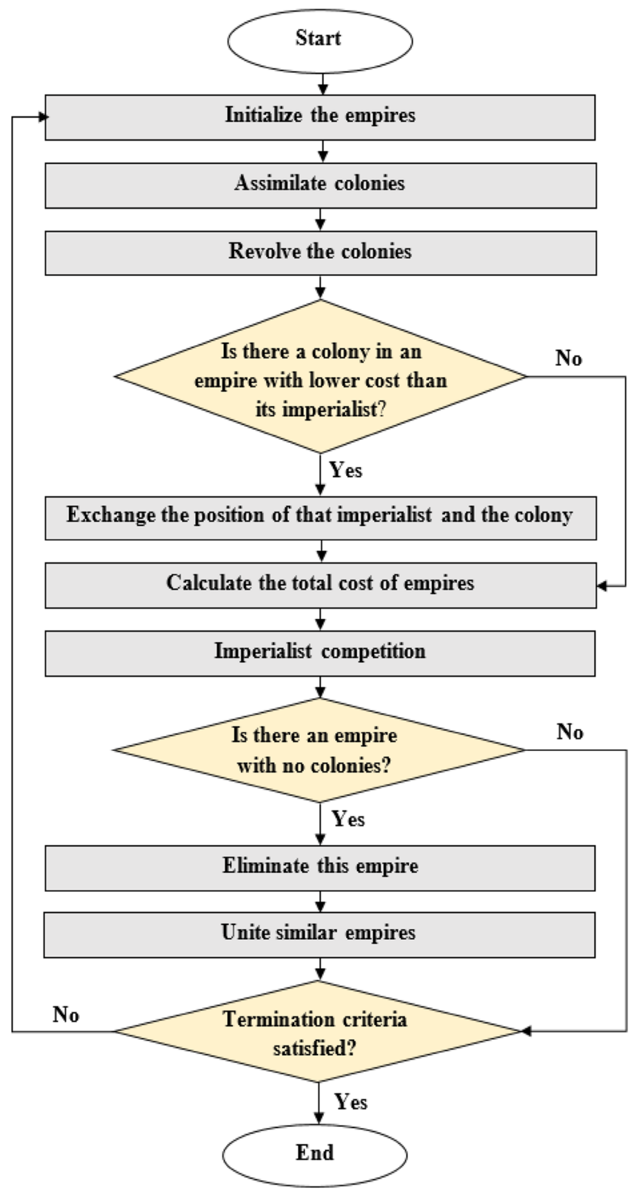

Fig. 1 ICA algorithm [50]

2.3 Hybrid algorithms

Literature consists of numerous studies attempting to enhance the performance quality of ANNs using the optimization algorithms such as ICA, particle swarm optimization (PSO), and GA [1, 51–56]. BP is known as an algorithm of local search learning; therefore, the optimum search process of ANN may fail to result in an efficient solution. As a result, the optimization algorithms are applicable to the adjustment of biases and weights of ANN in a way to enhance the quality of its performance. Concerning the local minimum in ANN systems, convergence is more probable, while optimization algorithms are capable of discovering a global minimum. Consequently, the hybrid systems (e.g., ICA-ANN) have the chance of using the search properties of ICA and ANN techniques. Within the search space, ICA can search for global minimum; ANN then uses it to find the best results of the whole system.

2.4 ANFIS

Jang [57] developed ANFIS as a soft computing technique incorporating fuzzy logic into neural networks. This technique has been extensively applied to engineering and earth sciences [58–61]. ANFIS is capable of simulating and analyzing the mapping relationships between input and output data by a hybrid learning in a way to properly identify the optimal distribution of membership function. As shown in Fig. 2, the base of this technique is the fuzzy "if-then" rules from the Takagi and Sugeno type [62]. This includes two different parts: a premise part and a consequent part. Figure 2 presents the equivalent ANFIS architecture from the Takagi and Sugeno type. In this inference system, it is consisted of five layers each of which contains a number of nodes described by the node function. The output signals released by the nodes existing within the preceding layers actually play the role of input signals in current layer. When the

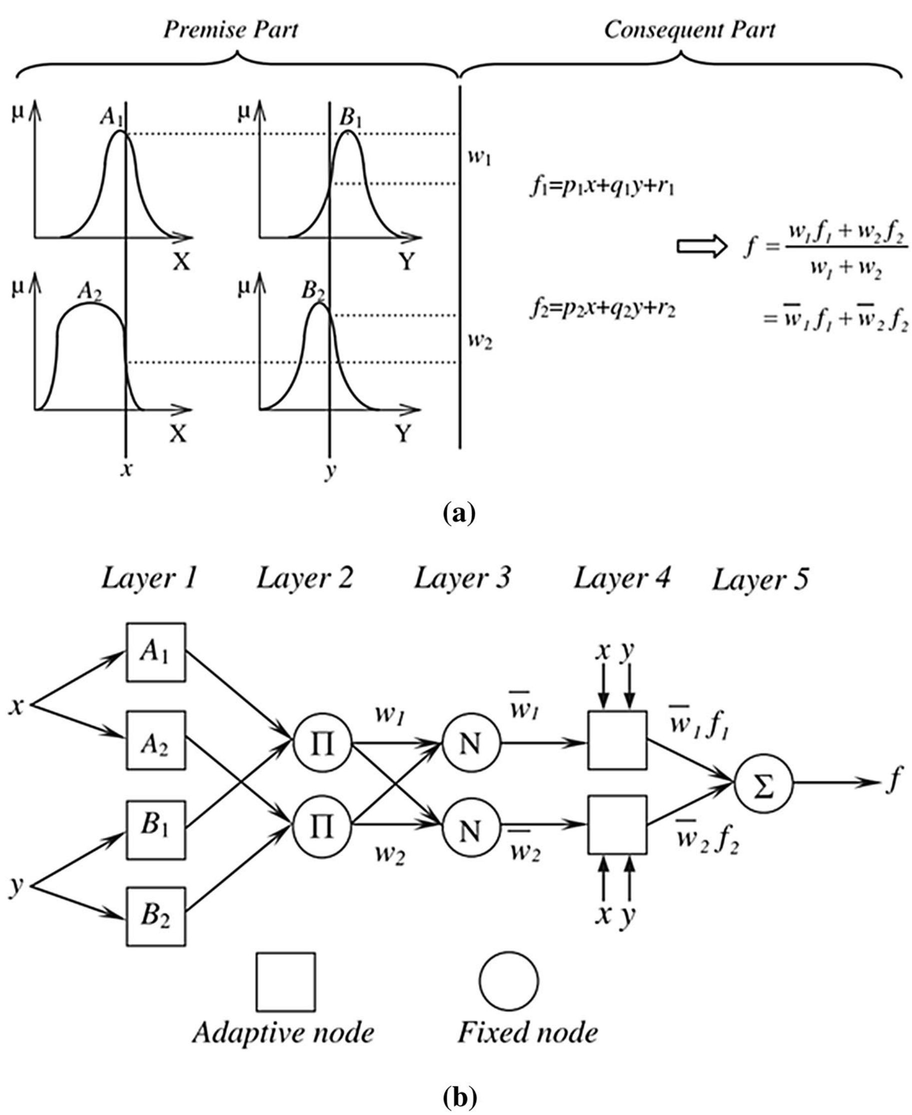

Fig. 2 Architecture of ANFIS [62]

output is manipulated in current layer by the node function, the output serves as input signals for the next layer. In this study, square nodes, also called adaptive nodes, are adopted to show that the parameter sets in these nodes can be well adjusted. On the other hand, the circle nodes, also called fixed nodes, are used to confirm that the parameter sets are completely fixed within the system. Referring to Jang [57], you can find a detailed explanation on the ANFIS procedure.

3 Database

In artificial intelligent techniques, there is a need to prepare an appreciate database for a better model development and model evaluation. To predict bearing capacity of the driven piles, the data sets used by Mohanty et al. [63], which is based on in situ driven pile load tests from the installed location, were selected. Therefore, to design intelligent techniques, 59 data sets (see Table 1) were considered where according to Swingler [43], 80% of that (47 data sets) were used for training the systems and 20% of that (12 datasets) was used for testing the systems. In these data sets, angle of shear resistance of soil at the shaft (φ shaft) and at the tip (φ tip) of the pile, effective overburden pressure ($\sigma' v$) at the tip of the pile, length of pile (L), and cross-sectional area of pile (A) were set as input parameters to estimate bearing capacity of the piles. The following section is related to designing intelligent systems of this study namely, ANN, ICA-ANN, and ANFIS techniques.

4 Designing intelligent models

4.1 ANN

In the present paper, the normalization of all data sets was done using the following equation:

$$X_{\text{norm}} = (X\_X_{\min})/(X_{\max}\_X_{\min}), \tag{1}$$

where X signifies the measured value, X_{norm} denotes the normalized value of the measured parameter; $X_{\max}$ and $X_{\min}$ stand for the maximum and minimum values of the measured parameters in the data set, respectively. The range of the normalized data is between (0 and 1) using Eq. 1. Considering the normalized data sets, it is expected to get higher performance prediction.

There are many training algorithms for ANN systems. Among them, Levenberg–Marquardt (LM) was selected and utilized to train the ANN systems. Many researchers have highlighted the efficiency of the LM algorithm (among other training algorithms) in solving engineering problems [9, 15, 64–66]. The optimal network architecture needs to be identified to accomplish the premier ANN performance. According to Hornik et al. [40], in the network architecture, a single hidden layer is capable estimating any continuous function. As a result, in the present paper, only one hidden layer was employed. Remember that, in the ANN architecture, the most important task is to choose the number of nodes in the hidden layer [67]. Several researchers have proposed a number of relations for the purpose of determining the number of nodes in hidden layers, while Hornik et al. [40] stated that the maximum number of hidden node is $\leq 2\times N_i + 1$ (Ni is number of input layers). Based on the number of input parameters, the number of nodes that need to be employed in the hidden layer will be varied from 1 to 11. The next step of the analysis needs to be involved in determining the optimum number of nodes in the hidden layer. Therefore, a parametric investigation was carried out on the optimum number of hidden nodes from 1 to 11. Several ANN models were designed and the best one among them was chosen according to R^2 results. The best R^2 results were obtained as 0.895 and 0.901 for model development and evaluation, respectively. These results were related to hidden node of 8. Therefore, an ANN structure of $5\times 8\times 1$ is suggested for the prediction of bearing capacity of driven piles. More discussion regarding the selected ANN model will be given later.

4.2 ICA-ANN

When modeling the ICA-ANN, parallel to hybrid ANN models, the key factors on ICA (as mentioned earlier, they are N_{country}, N_{imp}, and N_{decade}) need to be recognized and designed. Different values of N_{country} have been applied to the approximation of the problems related to geotechnical engineering. Ahmadi et al. [68], Marto et al. [69], and Hajihassani et al. [70] recommended the values of 40, 56, and 135, respectively, for N_{country}. Findings of the above-mentioned studies indicated that parametric research is required to achieve an appropriate value of N_{country}. As a result, a series of ICA-ANN analyses were carried out using different values of N_{countr} in a range between 25 and 500, in which N_{decade} was set to 200 and N_{imp} to 5. As indicated by findings, $N_{\text{country}} = 300$ is able to provide higher performance capacity of the ICA-ANN models compared to the other N_{country}. Thus, in modeling of bearing capacity of the driven piles, the value of 300 was chosen as optimum N_{country}.

The next stage of ICA-ANN involves obtaining the optimum N_{imp} with respect to another sensitivity analysis. To this end, N_{imp} was ranged between 5 and 65 to identify the best N_{imp} in modeling of bearing capacity of the driven piles. Results showed that $N_{\text{imp}} = 10$ outperformed the other values for the number of imperialists. Thus, optimum N_{imp} was set to 10. In the next stage of ICA-ANN modeling procedure, N_{decade} needs to be determined. To explore how N_{decade} affects the network performance, another parametric research

Table 1 Data used in intelligent designing, established by Mohanty et al. [63]

Test number	φ shaft	φ tip	$\sigma'v$ (kN/m^2)	L (m)	A (m²)	Q_m (total) (kN)
1	33	38	255	24.5	0.131	2615
2	34	37.5	206	19.8	0.223	36.75
3	33	38	223	21.5	0.131	2164
4	33	37.5	210	20.2	0.1468	3042
5	33	37	206	19.9	0.1821	2856
6	38	41	138	11.6	0.209	3558
7	38	40	164	13.7	0.209	3292
8	38	40	196	16.5	0.209	3923
9	35	37	158	16.2	0.105	1637
10	35	37	158	16.1	0.1644	2233
11	35	36.5	158	16.2	0.2109	2295
12	36.5	36.5	120	12.3	0.1654	1779
13	34	38	475	47.2	0.2917	5604
14	34	34	38	3	0.1644	712
15	35	35	72	6.1	0.1644	1735
16	35	35	100	8.9	0.1644	2491
17	36	36	131	12	0.1644	3158
18	36	36	161	15	0.1644	3825
19	35.5	36	163	15.2	0.1301	2695
20	34	38	146	11.3	0.0316	1429
21	35.5	35.5	89	9.1	0.0864	658
22	35.5	35.5	119	12.2	0.0864	882
23	35.5	35.5	148	15.2	0.0864	1014
24	35.5	35.5	178	18.3	0.0864	1281
25	35.5	35.5	89	9.1	0.0799	655
26	35.5	35.5	119	12.2	0.0799	894
27	35.5	35.5	148	15.2	0.0799	1113
28	35.5	35.5	178	18.3	0.0799	1281
29	31	31	134	16	0.0613	480
30	31	31	134	16	0.0613	519
31	33	33	111	12.2	0.0061	75
32	39	39.5	75	7	0.0999	2439
33	39	39.5	72	6.7	0.0999	3000
34	39	39.5	56	5.2	0.0999	1950
35	32	34	198	21	0.2313	3200
36	37.5	40	301	29.9	0.3075	4733
37	37.5	39.5	258	25.6	0.3075	4021
38	33	35	169	18	0.6568	5000
39	28	39	213	16.8	0.1431	4670
40	34	35	111	12.2	0.1143	854
41	32	35	241	23.3	0.1486	1628
42	34	35	92	9.1	0.1291	685
43	32	37	176	17.5	0.3855	3069
44	35	37	246	23.8	0.0729	1913
45	35	37	183	17.7	0.0729	2313
46	35	37	260	25.3	0.0729	1254
47	39	39.5	56	5.2	0.0999	1948
48	33	35.5	343	34.1	0.0325	1761
49	34	36	319	31.7	0.0325	2180
50	33	33	335	29.3	0.0557	3203
51	33	34	354	31.1	0.0557	3211

Table 1 (continued)

Test number	φ shaft	φ tip	$\sigma'v$ (kN/m^2)	L (m)	A (m²)	Q_m (total) (kN)
52	36	37	215	21.3	0.0409	1779
53	36	37	209	20.7	0.0827	1868
54	35	35	242	24.1	0.066	1779
55	36	37	209	207	0.0929	1913
56	35	35	166	16.5	0.0613	2100
57	35	35	178	17.7	0.0827	1509
58	35.5	37	228	21.9	0.066	922
59	35	35	178	17.7	0.0929	1779

required to be carried out. In this part, N_{decade} was fixed at 500. The results obtained from the use of different numbers of N_{decade} in the estimation of bearing capacity of the driven piles were based on RMSE. The results showed that no significant changes occurred to the network performance (RMSE) after setting N_{decade} to 400. Therefore, the optimum N_{decade} was fixed at 400 and results of this model were considered for the analysis of ICA-ANN model. R^2 values of 0.945 and 0.958 were achieved for training and testing of ICA-ANN model. It should be noted that the suggested ANN architecture ($5 \times 8 \times 1$) was considered in ICA-ANN models, as well.

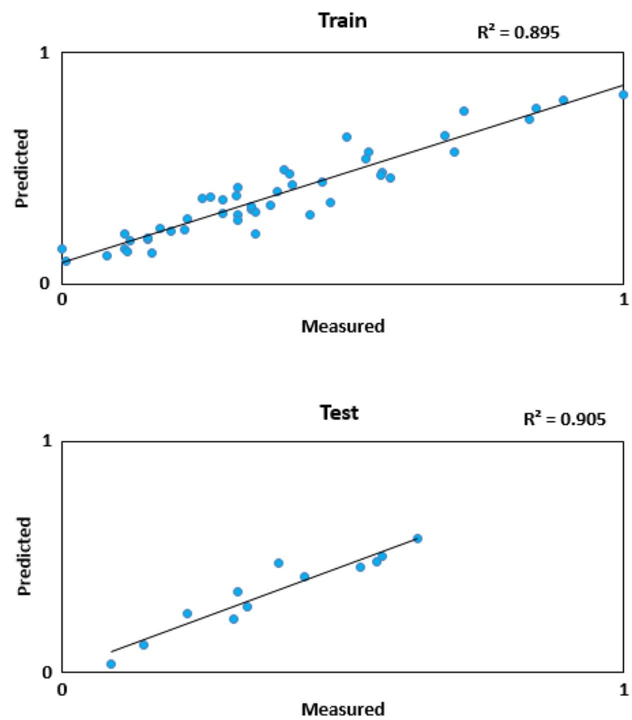

Fig. 3 Training and testing data sets modeled by ANN

4.3 ANFIS

This study attempts to provide an insight into applying ANFIS to the prediction of bearing capacity of the driven piles. The data sets needed for modeling, similar to the previous parts, were grouped randomly into two separate subsets: 80% for training the model and the rest of the data set was dedicated to testing purposes. The numbers of fuzzy rules, in the present paper, were set by means of a trial/error method. To do this, several models with a variety of fuzzy rule combinations (e.g., 2, 3, etc.) were employed. The final results confirmed that the ANFIS structure with three MFs for each input meaningfully outperformed RMSE. In general, as suggested by the findings of the parametric research, the model is expected to do its best prediction task in case the ANFIS model is trained with 243 fuzzy roles. To each of the inputs, an MF of the type of Gaussian was applied. This type of MF is the most popular MF in the field of fuzzy systems, since it brings both flexibility and simplicity [61, 71–73]. The linguistic variables allocated to input parameters are low (L), medium (M), and high (H) in the fuzzy rules. In addition, the type of output membership function was selected linear. Therefore, based on the mentioned structure, five ANFIS models were constructed and their performance was evaluated based on system error. Finally, the best ANFIS model with R^2 of 0.967 and 0.975 for training and testing data sets was found to predict bearing capacity of the driven piles. The MFs of the input, in the selected model, were adjusted after 9700 epochs by means of the hybrid optimization method that included BP for the

Table 2 Performance indices' results for the developed models

Model	RMSE		R^2		VAF	
	Train	Test	Train	Test	Train	Test
ANN	0.083	0.055	0.895	0.905	87.598	90.508
ANFIS	0.041	0.033	0.967	0.975	96.585	97.510
ICA-ANN	0.056	0.035	0.945	0.958	94.444	95.564

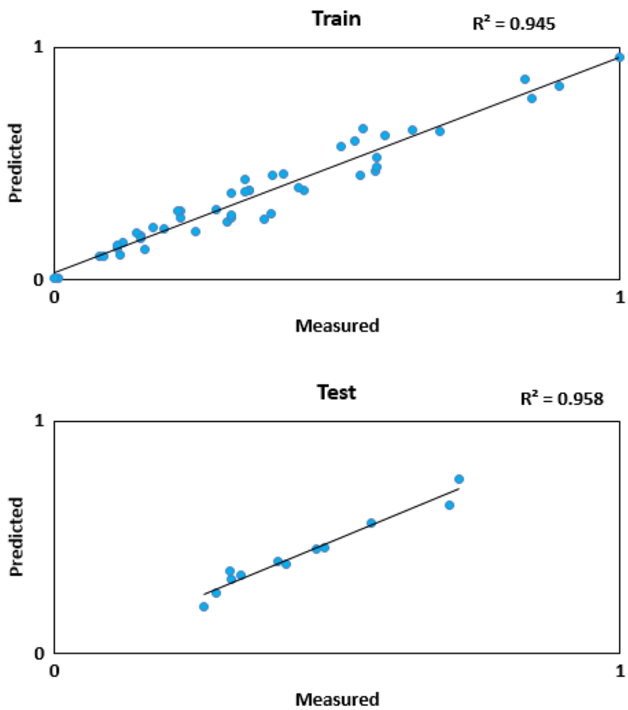

Fig. 4 Training and testing data sets modeled by ICA-ANN

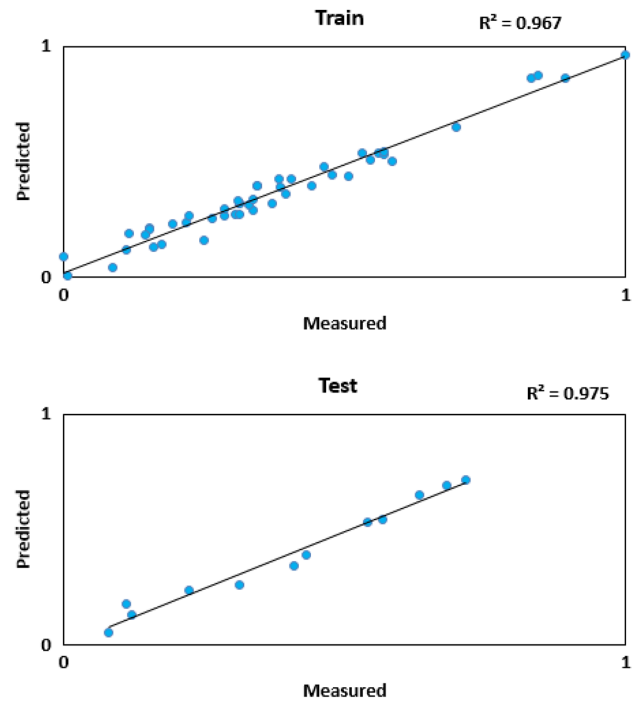

Fig. 5 Training and testing data sets modeled by ANFIS

parameters accompanied with the input MFs in addition to the estimation of least squares for those parameters that were accompanied with the output MFs. Remember that all ANFIS ANN and ICA-ANN models in this study were created by means of MATLAB software (version 7.14.0.739). To determine the RMSE values and do the statistical computations, we made use of the SPSS package (version 18.0).

5 Evaluation of the designed models

In this study, several intelligent techniques were selected, applied, and constructed for the purpose of prediction of pile bearing capacity based on established database comprising of 59 data sets. ANN together with two hybrid models, i.e., ICA-ANN and ANFIS, were designed in details considering the most effective parameters of these models. Then, based on the final structures of these models, many ANN, ANFIS, and ICA-ANN models were designed and the best models among them were selected according to only R^2 results. To evaluate the built models, two more performance indices (RMSE and variance account for, VAF) were considered where their equations are shown as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \left(y - y'\right)^2}{\sum_{i=1}^{N} (y - \tilde{y})^2}, \tag{2}$$

$$\text{VAF} = \left[1 - \frac{\text{var}(y - y')}{\text{var}(y)}\right] \times 100, \tag{3}$$

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y - y')^2}, \tag{4}$$

where y and y' are the predicted and measured values, respectively, $\tilde{y}$ is the mean of the y values, and N is the total number of data. The predictive technique will be excellent if $R^2 = 1$, VAF = 100, and RMSE = 0.

Table 2 shows the obtained results of performance indices for all the developed models. All results of VAF, RMSE, and R^2 for both training and testing data sets showed that two hybrid models receive a better performance prediction compared to pre-developed ANN model. RMES results of (0.083, 0.055), (0.041, 0.033), and (0.056, 0.035) were obtained for ANN, ANFIS, and ICA-ANN models, respectively, which showed that, by developing ANFIS models, a significant decrease in system error can be found. Therefore, ANFIS compared to the other proposed models can provide a better performance capacity in predicting bearing capacity of driven piles.

Figure 3,4, and 5 present the predicted and measured values of pile bearing capacity and their coefficients of determination by developing ANN, ICA-ANN, and ANFIS predictive approaches, respectively. As a result, R^2 values of (0.895, 0.905), (0.945, 0.958), and (0.967, 0.975) were

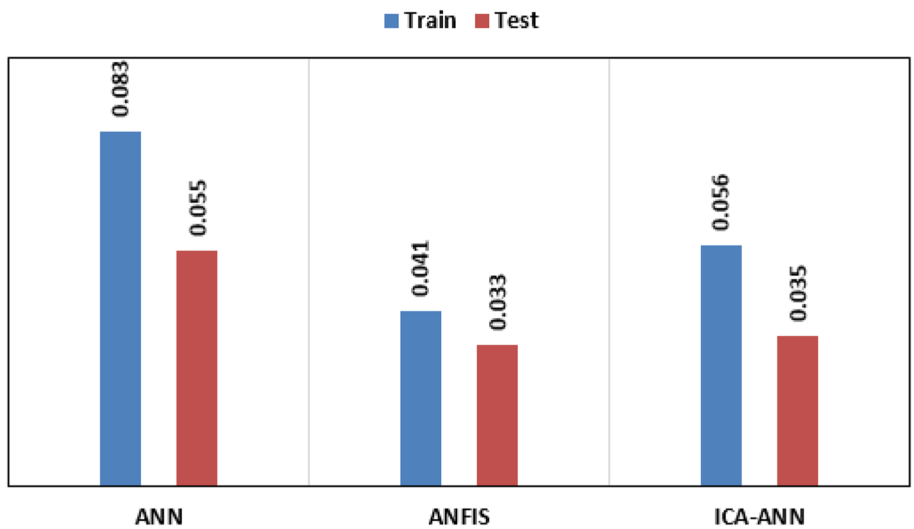

Fig. 6 Comparison of the RMSE results

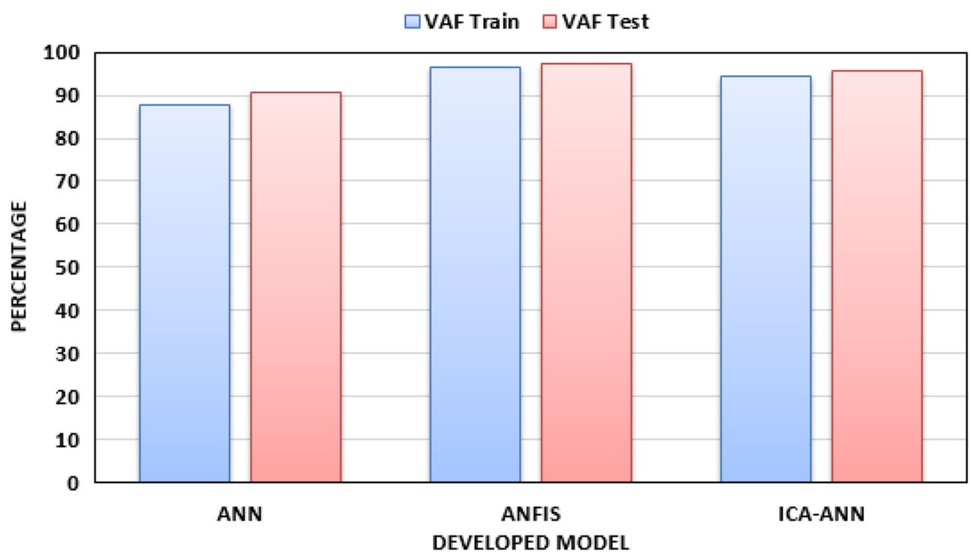

Fig. 7 Comparison of the VAF results

obtained for ANN, ICA-ANN, and ANFIS predictive techniques, respectively which showed that a difference of 0.7 can be found between ANN and ANFIS models. In addition, Figs. 6, 7 show the comparison of RMSE and VAF results, respectively, for ANN, ICA-ANN, and ANFIS models. Based on these figures, the best model with the minimum RMSE and the maximum VAF is related to ANFIS model. In fact, this model with assistance/advantage of both ANN and FIS techniques can perform better for solving problem of pile bearing capacity, and it can be introduced as a comprehensive model in the mentioned field.

6 Conclusions

In the present study, we apply three intelligent models (i.e., ANN, ANFIS, and ICA-ANN) to estimate the bearing capacity of driven piles. A database comprising a total of 59 datasets was provided. In each data set, φ shaft, φ tip, $\sigma' v$, L, and A were selected as inputs, while Q was set as the output of the system. All effecting parameters of each model were identified and applied for each model to receive higher performance capacity. Therefore, a series of parametric studies were conducted on the developed intelligent models by means of particular parameters of FIS, ICA, and ANN. As shown by the obtained results, both hybrid models were capable of significantly improving the performance prediction, though the ANFIS predictive model outperformed the ICA-ANN in terms of predicting the Q values. The obtained results of the developed models were as (0.895, 0.905), (0.945, 0.958), and (0.967, 0.975) for ANN, ICA-ANN, and ANFIS models, respectively, based on R^2. In addition, ANFIS model receives highest results of VAF and lowest results of RMSE among all the developed models in estimating pile bearing capacity. VAF values of 96.585 and 97.510 were obtained for training and testing of ANFIS model, and they are higher than results of ANN and ICA-ANN. It can be concluded that the ANFIS model would be the proper alternative as it combines the advantages of the ANN and FIS techniques to demonstrate a high prediction capacity in solving a mentioned problem in geotechnics.

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