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Prediction of suction caissons behavior in cohesive soils using computational intelligence methods

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ABSTRACT

Compared to drag anchors, suction caissons (Q) in clays often provide a cost-effective alternative for jacket structures, catenary, tension leg moorings, and taut leg. In this research, two computational approaches are proposed for predicting the uplift capacity of Q in clays. The proposed approaches are based on the combinations of adaptive network-based fuzzy inference system (ANFIS) models (ANFIS-subtractive clustering (ANFIS-SC) and ANFIS-fuzzy c-means (ANFIS-FC)) with metaheuristic techniques (ant colony optimization (ACO) or particle swarm optimization (PSO)). In these approaches, the PSO and ACO algorithms are employed to enhance the accuracy of ANFIS models. In order to develop hybrid models, a comprehensive database from open-source literature is used to train and test the proposed models. In these models, d (diameter of caisson), L (embedded length), D (depth), S_u (undrained shear strength of soil), θ (inclined angle), and T_k (load rate parameter) were used as the input parameters. The performance of all models was evaluated by comparing performance indexes, i.e., means squared error and squared correlation coefficient. As a result, PSO and ACO can be used as reliable algorithms to enhance the accuracy of ANFIS models. Moreover, it was found that the ANFIS– subtractive clustering-ACO model provides better results in comparison with other developed hybrid models.

Keywords : *ANFIS, PSO algorithm, ACO algorithm, fuzzy c-means clustering, suction caissons capacity, subtractive clustering*

1. Introduction

Suction caissons (Q) in clays can be designed in a way to be lighter than the steel required for an equivalent pile foundation [1] . A critical issue to the performance of Q is their uplift capacity. Various approaches have been utilized to find the uplift capacity of Q such as laboratory models [11; 25; 32], upper bound analyses [9], prototype model tests [8; 14], finite element methods [4; 16; 40; 42] and centrifuge models [10]. These studies have tried to understand the lateral and axial load capacity of Q. The importance of the uplift capacity of Q implies a need to develop a robust model to evaluate this factor. For this purpose, ANFIS, which is a computational intelligence method, integrates the fuzzy inference system (FIS) concept into the artificial neural network (ANN). This method has been widely used in the field of civil and mining engineering [19; 21; 33; 41]. Mapping the relationship between output and input variables through training for the determination of the membership function (MF) can be evaluated uaing ANFIS. This technique is a strong methodology for simulating complex relationships between inputs and outputs. However, in ANFIS models, a series of parameters exist that are required to be chosen by the user. Therefore, for these parameters, it is essential to apply metaheuristic algorithms for searching the suitable value [27; 37]. In the present paper, the proposed approaches are based on hybrid ANFIS models (ANFIS- FC and ANFIS-SC) with ACO and PSO. In ANFIS models, the PSO and ACO algorithms are applied to enhance the accuracy of ANFIS models. In hybrid approaches, PSO and ACO are used to optimize and tune the values of antecedent and consequent parameters of the ANFIS models.

2. Materials and methods

In this part, first, a literature review of ANFIS, SC, and FC methods is presented, and then, some descriptions about the PSO and ACO algorithms are provided as well.

2.1. ANFIS

An ANFIS approach [22] is a combination of neural learning and Sugeno fuzzy to capture the input–output relationship. The structure of a two-input ANFIS approach is presented in Fig. 1.

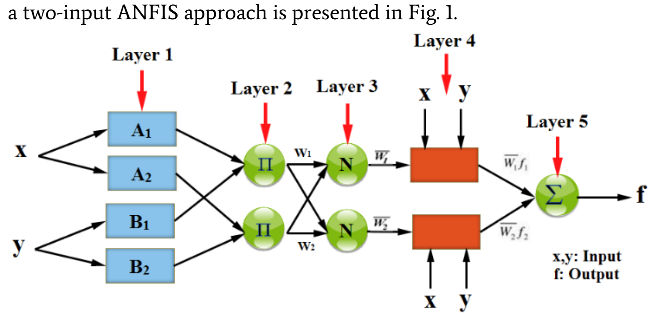

Fig. 1 The structure of a two-input ANFIS approach (after [22]).

Layer 1 is responsible for the fuzzification [39] :

$$Q_i^1 = \mu_{Ai}(x) = \frac{1}{1+\left[\left(\frac{x-v_i}{\sigma_i}\right)^2\right]^{b_i}} \tag{1}$$

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Where, $\{\sigma_i, V_i, b_i\}$ is a series of parameters influencing the membership function (MF); Ai is the linguistic label, and x is the input.

Layer 2 is [22] :

$$Q_i^2 = W_i = \mu_{Ai}(x).\mu_{Bi}(y) \qquad i = 1,2 \tag{2}$$

Layer 3 as follows [22] :

$$Q_i^3 = \bar{W}_i = \frac{w_i}{\sum_{j=1}^{2} w_j}, \qquad i = 1,2 \tag{3}$$

Where, w_i is the firing strength of the i^{th} rule computed in Layer 2.

Layer 4 as follows [39] :

$$Q_i^4 = \bar{W}_i f_i = \bar{W}_i (p_i x + q_i y + r_i) \tag{4}$$

where, $\bar{W}_i$ is the output of layer 3.

Layer 5 is the output layer, summed as:

$$Q_i^5 = Overall\ Output = \sum \bar{W}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{5}$$

Different ANFIS models can be built using different identification methods and for a given data set. In this paper, in order to identify the antecedent MFs, SC and FC are two methods used. Further details on the SC method can be found in Chiu [7]. Also, more information about the FC method can be found in Bezdek [3].

2.2. ACO algorithm

ACO was first suggested by Dorigo [13]. In this algorithm, each artificial ant builds a tour using frequently applying a stochastic greedy rule;

$$P(r,u) = \begin{cases} \arg\max_{u \in J(r)} \left\{ [\tau(r,u)]^{\alpha} . [\tau(r,u)]^{\beta} \right\}, & if \ \ q \le q_0 \\ S & , \ otherwise \end{cases} \tag{11}$$

(r,u): the edge between point u and r; $\tau(r,u)$ stands for the pheromone; and $\eta(r,u)$ is the edge desirability. q is a random number, and q_0 is $0 \le q_0 \le 1$ (user-defined parameter).

for local updating rule;

$$\tau(r,s) \leftarrow (1-\rho).\tau(r,s) + \rho\tau_0 \tag{13}$$

ρ: pheromone evaporation ($0<\rho<1$).

for global updating rule;

$$\tau(r,s) \leftarrow (1-\delta).\tau(r,s) + \Delta\tau(r,s) \tag{14}$$

where;

$$\Delta\tau(r,s) = \begin{cases} 1/L_{gb}, & if \ (r,s) \in global \ best \ tour \\ 0, & otherwise \end{cases} \tag{15}$$

δ ($0<\delta<1$) is the global pheromone decay parameter, $\Delta\tau(r,s)$ is used to increase the pheromone and L_{gb} is the length of the globally best tour [43]. Further details on ACO can be found in [12].

2.3. PSO algorithm

The PSO algorithm was firstly proposed by Eberhart and Kennedy [15]. The particle moves around according to its position and velocity at each iteration. Each particle position is updated by its velocity vector, as presented in Eq. (17).

$$V_i^{t+1} = \omega V_i^t + C_1 r_1^t (P_i^t - X_i^t) + C_2 r_2^t (P_g^t - X_i^t) \tag{16}$$

$$X_i^{t+1} = X_i^t + V_i^{t+1} \tag{17}$$

where, V_i^t : velocity vector, P_i^t : the global best position; r_1 and r_2 represent random numbers ($0< r_1$ and $r_2<1$); C_1: cognitive parameter; ω: inertia weight; C_2: social parameter and P_g^t denotes the best particle position [35].

2.4. ANFIS trained by PSO or ACO

In this research study, a similar methodology was inspired by the works carried out by [2; 5; 6; 17; 18; 20; 23; 24; 26; 28; 29; 30; 34; 36; 38]. Fig. 2 shows the process of training ANFIS models with ACO or PSO.

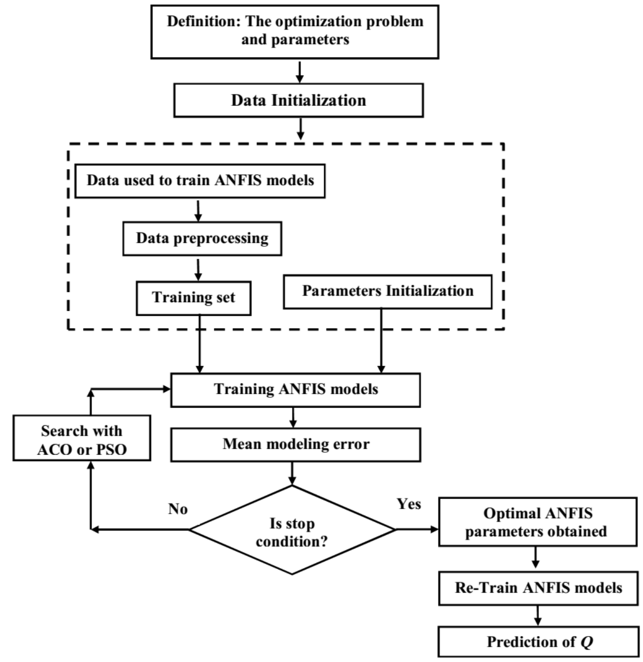


Fig. 2. The process of training ANFIS models with ACO or PSO.

3. Experimental database

The database contains 62 experimental test results, including field test results and laboratory-scale models gathered by Rahman, Wang, Deng, and Carter [31]. The database includes several variable measurements such as d (diameter of caisson), L (embedded length), D (depth), S_u (undrained shear strength of soil), θ (inclined angle) and T_k (load rate parameter) and Q. A detailed information on the database can be found in section 2.1 from [31]. In this paper, all data were randomly divided into two subsets: 80% (training data) for model construction and 20% (testing data) for assessing the accuracy of the model.

4. Evaluation criteria

In this paper, two statistical criteria viz. squared correlation coefficient (R^2) and the mean squared error (MSE) were chosen to be a measure of reliability (Eqs. 18 and 19), in which t_k: actual value, $\hat{t}_k$: estimated value, and n: observations number.

$$MSE = \frac{1}{n} \sum_{k=1}^{n} (t_k - \hat{t}_k)^2 \tag{18}$$

$$R^2 = 1 - \frac{\sum_{k=1}^{n} (t_k - \hat{t}_k)^2}{\sum_{k=1}^{n} t_k^2 - \frac{\sum_{i=1}^{n} \hat{t}_k^2}{n}} \tag{19}$$

5. Prediction of uplift capacity of Q

The optimization made using the ACO or PSO algorithms meaningfully improved the capability of ANFIS. The choice of PSO or ACO algorithm parameters plays a significant role in optimization. Table 1 presents both of the applied ACO and PSO algorithm parameters. The ACO and PSO parameters presented in the table were chosen based on trial-and-error.

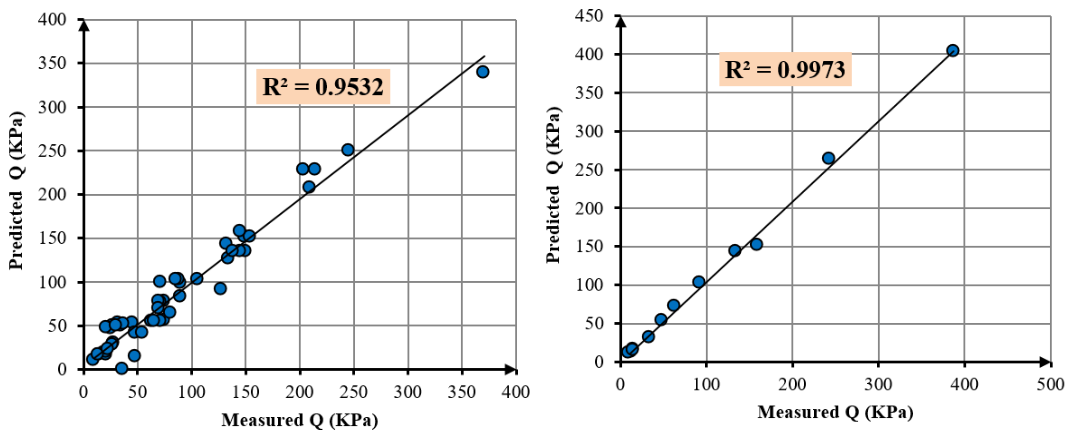
These models used to build an estimation model for the prediction of Q using MATLAB. In these models, the L/d, θ, S_u, D/L, and T_k were used as the input parameters. Correlations between the estimated and actual Q values for the testing and training data are presented in Figs. 3 to 6. Also, a comparison between the estimated and actual Q values for the testing and training data is presented in Figs. 7 to 10.

As shown in Figs. 3 to 10, in comparison with measured data, the results of the ANFIS-ACO-SC model show excellent precision.

In addition, we compared the results obtained by Rahman et al. [31] with our results. This comparison is shown in Table 2.

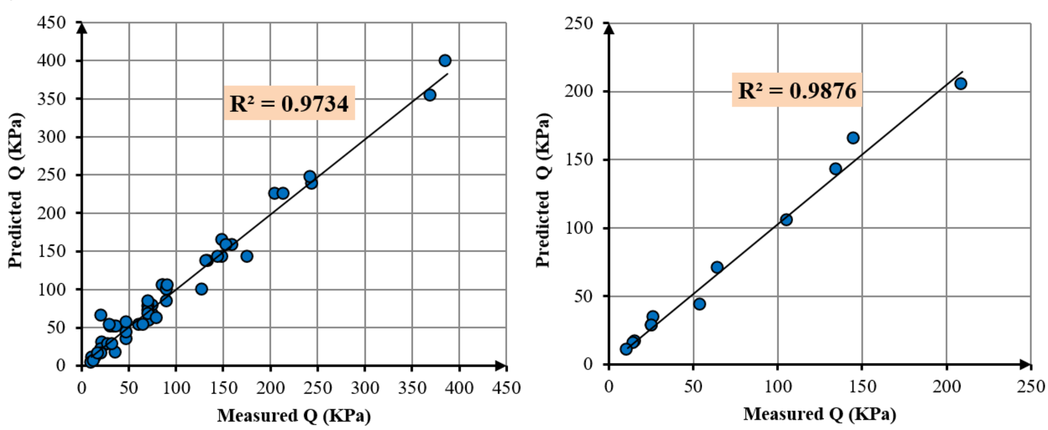
Table 1: PSO and ACO algorithm parameters.

PSO parameters	ACO parameters
Population size=25	The number of ants =20
Maximum number of iterations=200	Iterations number =200
ω =1	Pheromone intensity=100
Damping ratio of inertia weight =0.99	Important factor of utility=4
C_1= 1	Important factor of evaporation =1
C_2= 2	ρ=0.1
	τ=100



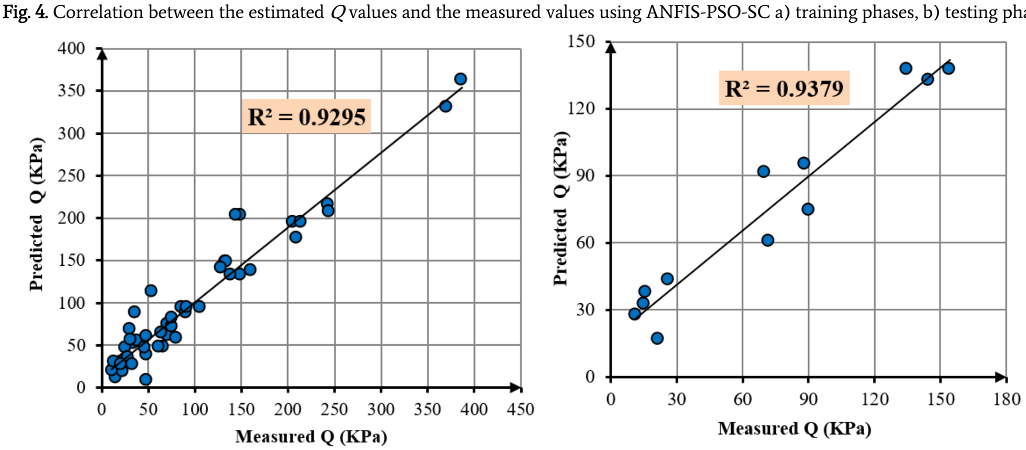
(a) (b)

Fig. 3. Correlation between the estimated Q values and the measured values using ANFIS-ACO-SC a) training phases, b) testing phases.



(a) (b)

Fig. 4. Correlation between the estimated Q values and the measured values using ANFIS-PSO-SC a) training phases, b) testing phases.



(a) (b)

Fig. 5. Correlation between the estimated Q values and the measured values using ANFIS-ACO-FC a) training phases, b) testing phases.

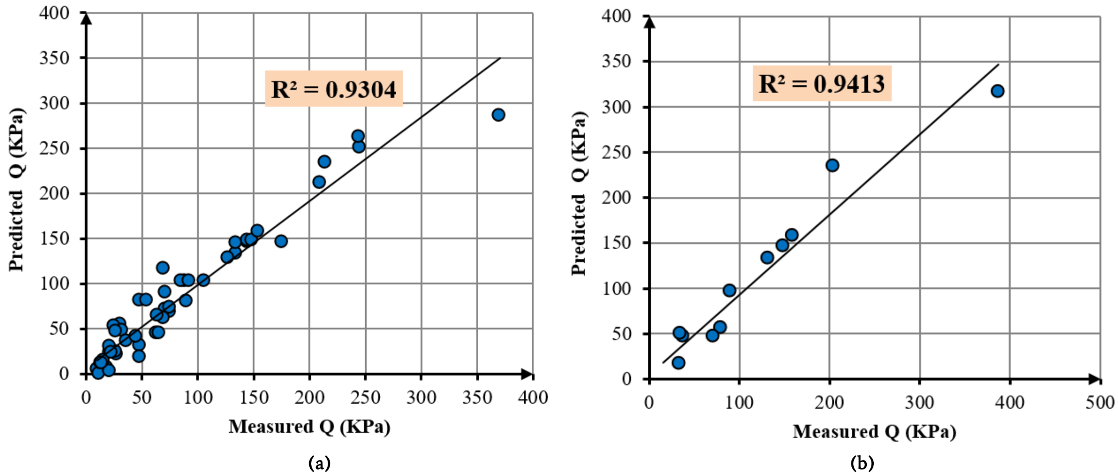


Fig. 6. Correlation between the estimated *Q* values and the measured values using ANFIS-PSO-FC a) training phases, b) testing phases.

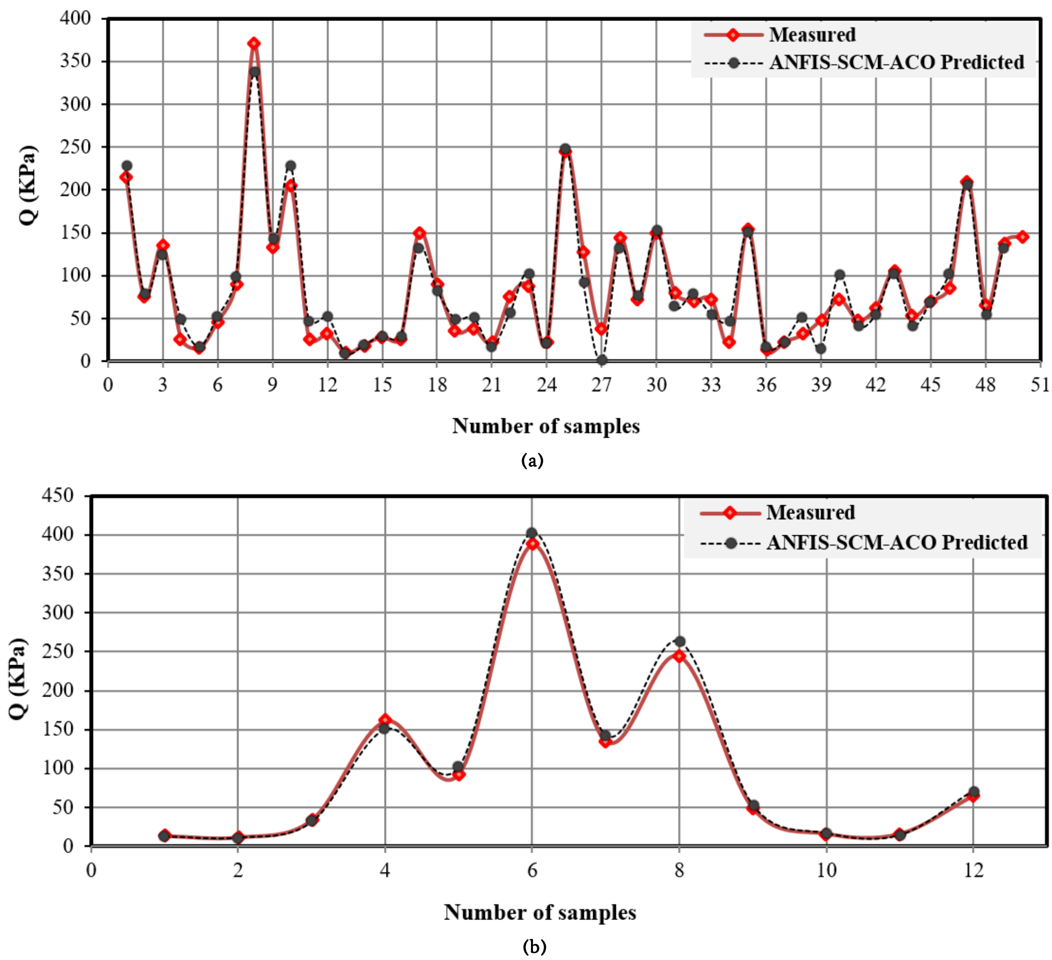


Fig. 7. Comparison between the estimated and measured *Q* values using ANFIS-ACO-SC a) training phases, b) testing phases.

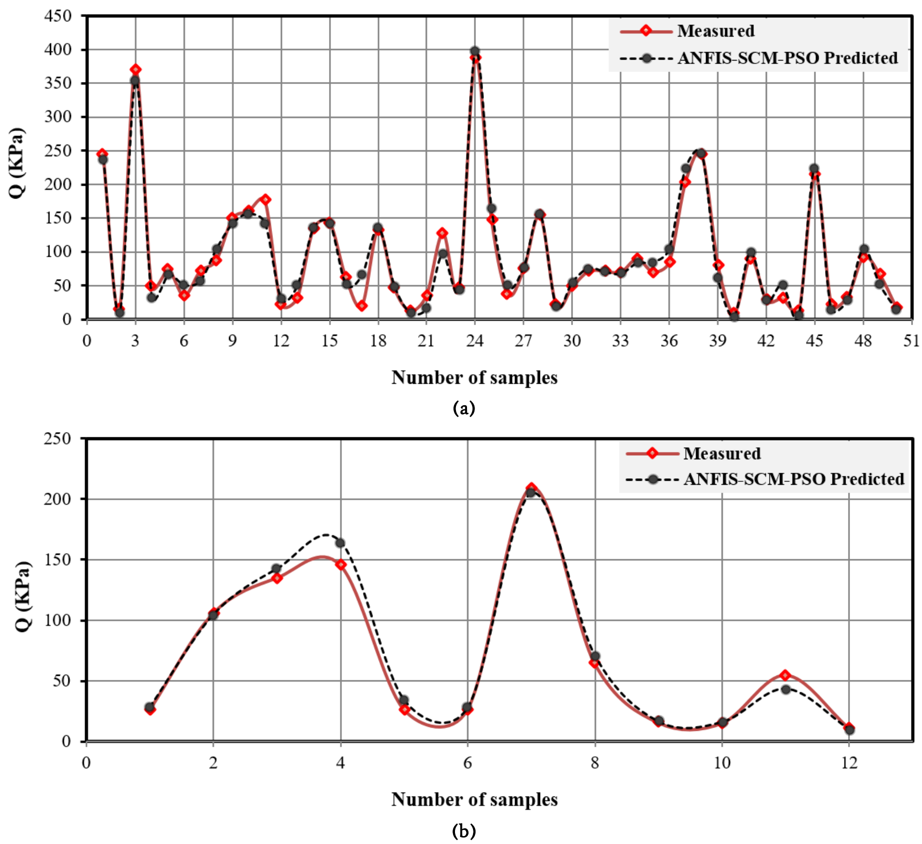


Fig. 8. Comparison between the estimated and measured Q values using ANFIS-PSO-SC a) training phases, b) testing phases.

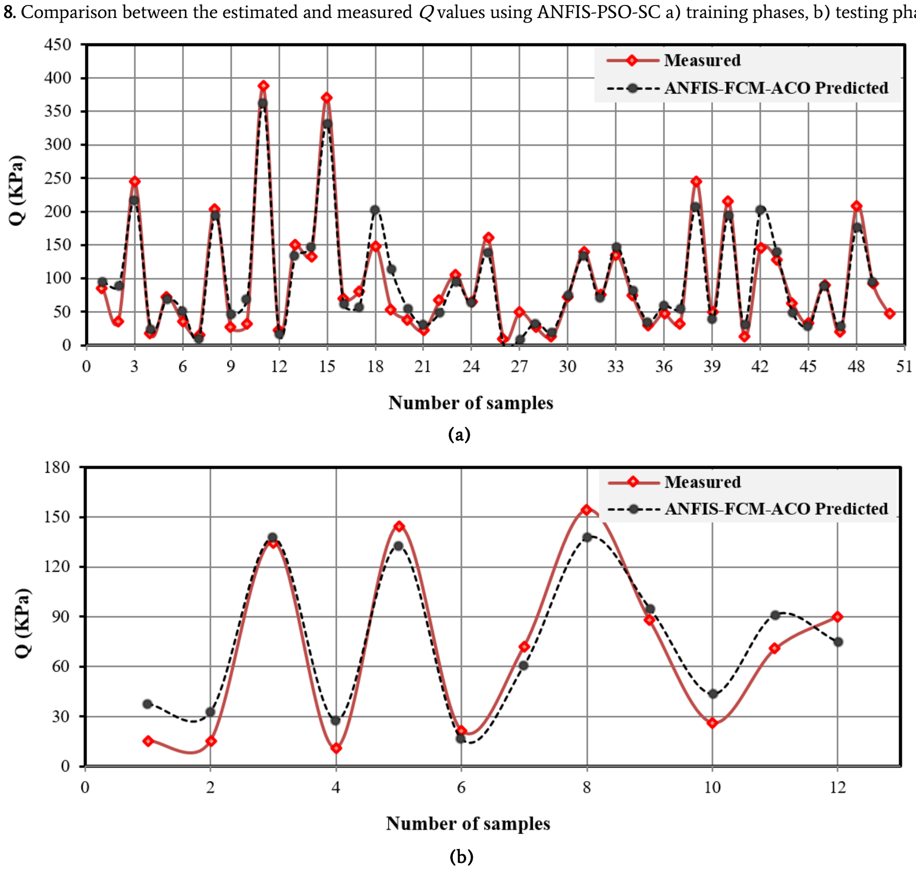


Fig. 9. Comparison between the actual and estimated Q values using ANFIS-ACO-FC a) training phases, b) testing phases.

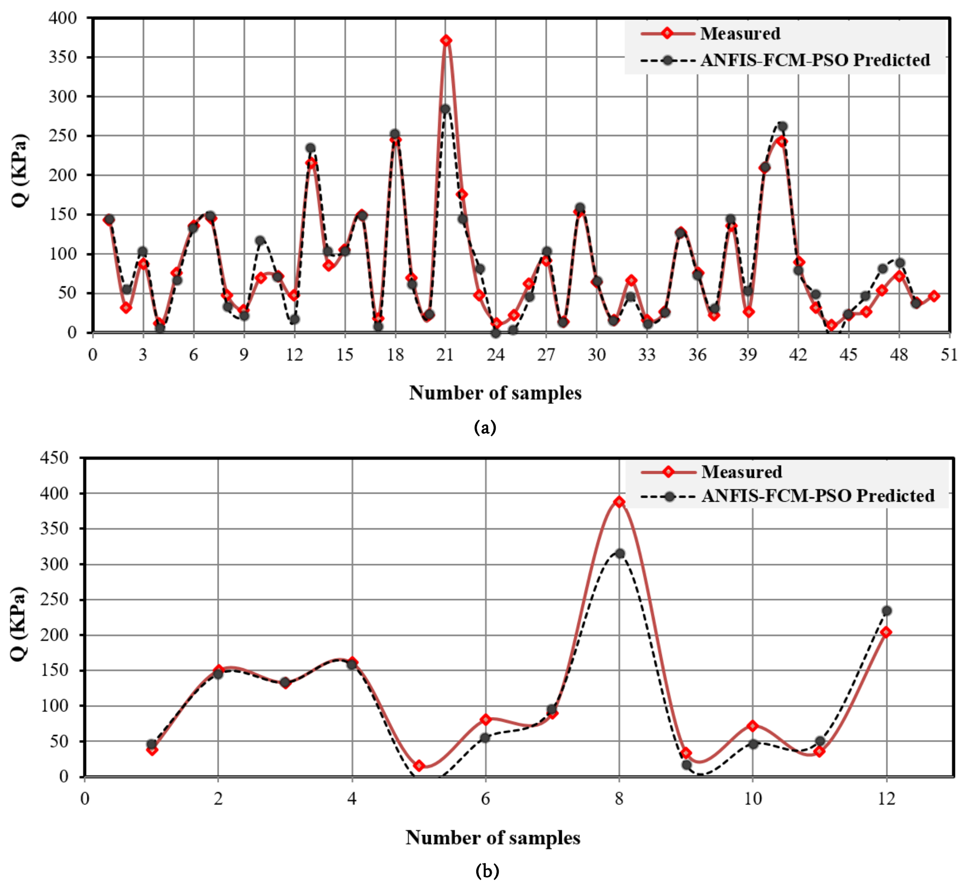


Fig. 10. Comparison between the estimated and measured *Q* values using ANFIS-PSO-FC a) training phases, b) testing phases.

Table 2. Comparison of the performance of the previously presented model and the proposed models in this study.

Description		MSE	R^2
ANFIS-SC-ACO	Training phases	0.0066	0.9532
(Proposed in this paper)	Testing	0.0022	0.9973
ANFIS-SC-PSO	Training phases	0.0053	0.9734
(Proposed in this paper)	Testing phases	0.0015	0.9876
ANFIS-SC	Training phases	0.0096	0.9478
(Proposed in this paper)	Testing phases	0.0033	0.9836
ANFIS-FC-ACO	Training phases	0.0149	0.9295
(Proposed in this paper)	Testing phases	0.0061	0.9379
ANFIS-FC-PSO	Training phases	0.0108	0.9304
(Proposed in this paper)	Testing phases	0.0195	0.9413
ANFIS-FC	Training phases	0.0150	0.9011
(Proposed in this paper)	Testing phases	0.0308	0.9155
ANN	Training phases	-----	-----
(Proposed in [31])	Testing phases	0.0339	0.9721

As seen, the ANFIS-ACO-SC model indicates better results relative to the previously presented model. As Table 2 shows, ANFIS-ACO-SC was found to be the best model with R^2=0.9973 and MSE=0.0022.

6. Conclusions

Reliable assessment of the uplift capacity of *Q* in clays is a critical challenge for design engineers. In this paper, ANFIS models (ANFIS–FC-ACO, ANFIS–FC-PSO, ANFIS–SC-ACO, ANFIS–SC-PSO, ANFIS–FC, and ANFIS–SC) were applied to predict Q. In these models, the *L/d*, θ, S_u, *D/L*, and T_k were used as the input parameters. Optimization increased the accuracy of ANFIS models. The optimization algorithms applied for improving the accuracy of ANFIS models were PSO and ACO. The following conclusions were made:

- Among the two algorithms (PSO and ACO) applied for training ANFIS, ACO showed a better performance.
- All suggested models in this paper were able to successfully estimate *Q*.
- According to the training and testing error values, ANFIS–FC-ACO, ANFIS–FC-PSO, ANFIS–SC-ACO, and ANFIS–SC-PSO performed better than ANFIS–FC and ANFIS–SC.
- The comparison between the previously presented model and the proposed models in this study revealed the superiority of ANFIS–SC-ACO in the estimation of *Q*.

Applying optimization algorithms meaningfully increased the accuracy of finding optimal values of ANFIS.

REFERENCES

[1] Alavi, A. H., Aminian, P., Gandomi, A. H., & Esmaeili, M. A. (2011). Genetic-based modeling of uplift capacity of suction caissons. *Expert Systems with Applications, 38*(10), 12608-12618.

[2] Anemangely, M., Ramezanzadeh, A., & Tokhmechi, B. (2017). Shear wave travel time estimation from petrophysical logs using ANFIS-PSO algorithm: A case study from Ab-Teymour Oilfield. *Journal of Natural Gas Science and Engineering, 38*, 373-387.

[3] Bezdek, J. C. (1973). Fuzzy mathematics in pattern classification. Ithaca: Cornell University.

[4] Cao, J., Audibert, J., Al-Khafaji, Z., Phillips, R., & Popescu, R. (2002). *Penetration resistance of suction caissons in clay.* Paper presented at the The Twelfth International Offshore and Polar Engineering Conference.

[5] Catalão, J. P. d. S., Pousinho, H. M. I., & Mendes, V. M. F. (2010).

Hybrid wavelet-PSO-ANFIS approach for short-term electricity prices forecasting. *IEEE transactions on power systems, 26*(1), 137-144.

[6] Chen, M.-Y. (2013). A hybrid ANFIS model for business failure prediction utilizing particle swarm optimization and subtractive clustering. *Information Sciences, 220*, 180-195.

[7] Chiu, S. L. (1994). Fuzzy model identification based on cluster estimation. *Journal of intelligent and Fuzzy systems, 2*(3), 267-278.

[8] Cho, Y., Lee, T., Park, J., Kwag, D., Chung, E., & Bang, S. (2002). *Field tests on suction pile installation in sand.* Paper presented at the ASME 2002 21st International Conference on Offshore Mechanics and Arctic Engineering.

[9] Clukey, E., Morrison, M., Gamier, J., & Corté, J. (1995). *The response of suction caissons in normally consolidated TLP loading conditions.* Paper presented at the Offshore Technology Conference.

[10] Clukey, E. C., & Morrison, M. J. (1993). *A centrifuge and analytical study to evaluate suction caissons for TLP applications in the Gulf of Mexico.* Paper presented at the Design and performance of deep foundations: Piles and piers in soil and soft rock.

[11] Datta, M., & Kumar, P. (1996). *Suction beneath cylindrical anchors in soft clay.* Paper presented at the The Sixth International Offshore and Polar Engineering Conference.

[12] Dorigo, M., Birattari, M., & Stutzle, T. (2006). Ant colony optimization. *Computational Intelligence Magazine, IEEE, 1*(4), 28-39.

[13] Dorigo, M., & Blum, C. (2005). Ant colony optimization theory: A survey. *Theoretical computer science, 344*(2), 243-278.

[14] Dyvik, R., Andersen, K. H., Hansen, S. B., & Christophersen, H. P. (1993). Field tests of anchors in clay. I: Description. *Journal of Geotechnical engineering, 119*(10), 1515-1531.

[15] Eberhart, R., & Kennedy, J. (1995). *A new optimizer using particle swarm theory.* Paper presented at the Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on.

[16] El-Gharbawy, S., & Olson, R. (2000). *Modeling of suction caisson foundations.* Paper presented at the The Tenth International Offshore and Polar Engineering Conference.

[17] Ghasemi, E., Kalhori, H., & Bagherpour, R. (2016). A new hybrid ANFIS–PSO model for prediction of peak particle velocity due to bench blasting. *Engineering with Computers, 32*(4), 607-614.

[18] Ghomsheh, V. S., Shoorehdeli, M. A., & Teshnehlab, M. (2007). *Training ANFIS structure with modified PSO algorithm.* Paper presented at the 2007 Mediterranean Conference on Control & Automation.

[19] Grima, M. A., Bruines, P., & Verhoef, P. (2000). Modeling tunnel boring machine performance by neuro-fuzzy methods. *Tunnelling and Underground Space Technology, 15*(3), 259-269.

[20] Hasanipanah, M., Amnieh, H. B., Arab, H., & Zamzam, M. S. (2018). Feasibility of PSO–ANFIS model to estimate rock fragmentation produced by mine blasting. *Neural Computing and Applications, 30*(4), 1015-1024.

[21] Iphar, M., Yavuz, M., & Ak, H. (2008). Prediction of ground vibrations resulting from the blasting operations in an open-pit mine by adaptive neuro-fuzzy inference system. *Environmental geology, 56*(1), 97-107.

[22] Jang, J.-S. (1993). ANFIS: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics, 23*(3), 665-685.

[23] Jiang, H., Kwong, C., Ip, W., & Wong, T. (2012). Modeling customer satisfaction for new product development using a PSO-based ANFIS approach. *Applied Soft Computing, 12*(2), 726-734.

[24] Kaveh, A., Hamze-Ziabari, S., & Bakhshpoori, T. (2018). Feasibility of PSO-ANFIS-PSO and GA-ANFIS-GA models in prediction of peak ground acceleration. *International Journal of Optimization in Civil Engineering, 8*(1), 1-14.

[25] Larsen, P. (1989). *Suction anchors as an anchoring system for floating, offshore constructions.* Paper presented at the Offshore Technology Conference.

[26] Lin, C.-J., & Hong, S.-J. (2007). The design of neuro-fuzzy networks using particle swarm optimization and recursive singular value decomposition. *Neurocomputing, 71*(1-3), 297-310.

[27] Meysam Mousavi, S., Tavakkoli-Moghaddam, R., Vahdani, B., Hashemi, H., & Sanjari, M. (2013). A new support vector model-based imperialist competitive algorithm for time estimation in new product development projects. *Robotics and Computer-Integrated Manufacturing, 29*(1), 157-168.

[28] Oliveira, M. V. d., & Schirru, R. (2009). Applying particle swarm optimization algorithm for tuning a neuro-fuzzy inference system for sensor monitoring. *Progress in Nuclear Energy, 51*(1), 177-183.

[29] Pousinho, H. M. I., Mendes, V. M. F., & Catalão, J. P. d. S. (2011). A hybrid PSO–ANFIS approach for short-term wind power prediction in Portugal. *Energy Conversion and Management, 52*(1), 397-402.

[30] Pousinho, H. M. I., Mendes, V. M. F., & Catalão, J. P. d. S. (2012). Short-term electricity prices forecasting in a competitive market by a hybrid PSO–ANFIS approach. *International Journal of Electrical Power & Energy Systems, 39*(1), 29-35.

[31] Rahman, M., Wang, J., Deng, W., & Carter, J. (2001). A neural network model for the uplift capacity of suction caissons. *Computers and Geotechnics, 28*(4), 269-287.

[32] Rao, S. N., Ravi, R., & Ganapathy, C. (1997). *Pullout behavior of model suction anchors in soft marine clays.* Paper presented at the The Seventh International Offshore and Polar Engineering Conference.

[33] Sezer, E. A., Nefeslioglu, H. A., & Gokceoglu, C. (2014). An assessment on producing synthetic samples by fuzzy C-means for limited number of data in prediction models. *Applied Soft Computing, 24*, 126-134.

[34] Shahlaei, M., Madadkar-Sobhani, A., Saghaie, L., & Fassihi, A. (2012). Application of an expert system based on Genetic Algorithm–Adaptive Neuro-Fuzzy Inference System (GA–ANFIS) in QSAR of cathepsin K inhibitors. *Expert Systems with Applications, 39*(6), 6182-6191.

[35] Shi, Y., & Eberhart, R. (1998). *A modified particle swarm optimizer.* Paper presented at the Evolutionary Computation Proceedings, IEEE World Congress on Computational Intelligence.

[36] Shoorehdeli, M. A., Teshnehlab, M., & Sedigh, A. (2006). *A novel training algorithm in ANFIS structure.* Paper presented at the 2006 American Control Conference.

[37] Üstün, B., Melssen, W., Oudenhuijzen, M., & Buydens, L. (2005). Determination of optimal support vector regression parameters by genetic algorithms and simplex optimization. *Analytica Chimica Acta, 544*(1), 292-305.

[38] Ustun, S. V., & Demirtas, M. (2009). Modeling and control of V/f

controlled induction motor using genetic-ANFIS algorithm. *Energy Conversion and Management, 50*(3), 786-791.

[39] Weiling, C., & Lee, J. (1995). *Fuzzy Logic for the Applications to Complex Systems*. Paper presented at the Proceedings of the International Joint Conference of CFSA/IFIS/SOFT on Fuzzy Theory and Applications. Singapore et al.: World Scientific.

[40] Whittle, A. J., & Kavvadas, M. J. (1994). Formulation of MIT-E3 constitutive model for overconsolidated clays. *Journal of Geotechnical engineering, 120*(1), 173-198.

[41] Yilmaz, I., & Yuksek, G. (2009). Prediction of the strength and elasticity modulus of gypsum using multiple regression, ANN, and ANFIS models. *International Journal of Rock Mechanics and Mining Sciences, 46*(4), 803-810.

[42] Zdravković, L., Potts, D., & Jardine, R. (2001). A parametric study of the pull-out capacity of bucket foundations in soft clay. *Geotechnique, 51*(1), 55-67.

[43] Zeng, D. H., Liu, Y., Jiang, L. B., Li, L., & Xu, G. (2012). *A New Approach to Cutting Temperature Prediction Using Support Vector Regression and Ant Colony Optimization*. Paper presented at the Advanced Engineering Forum.