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Pile bearing capacity estimation using GEP, RBFNN and MVNR techniques

Hooman Harandizadeh[1], Danial Jahed Armaghani*[2] and Vahid Toufigh[3]

[1]*Department of Civil Engineering. Faculty of Engineering. Shahid Bahonar University of Kerman. Pajoohesh Sq. Imam Khomeni Highway. P.O. Box 76169133. Kerman, Iran*
[2]*Department of Civil Engineering. Faculty of Engineering. University of Malaya. 50603. Kuala Lumpur, Malaysia*
[3]*Faculty of Civil and Surveying Engineering. Graduate University of Advanced Technology. Kerman, Iran*

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Abstract. This study introduced a new predictive approach for estimating the bearing capacity of driven piles. To this end, the required data based on literature such as hammer strikes, soil properties, geometry of the pile, and friction angle between pile and soil were gathered as a suitable database. Then, three predictive models i.e., gene expression programming (GEP), radial basis function type neural networks (RBFNN) and multivariate nonlinear regression (MVNR) were applied and developed for pile bearing capacity prediction. After proposing new models, their performance indices i.e., root mean square error (RMSE) and coefficient of determination (R2) were calculated and compared to each other in order to select the best one among them. The obtained results indicated that the RBFNN model is able to provide higher performance prediction level in comparison with other predictive techniques. In terms of R2, results of 0.9976, 0.9466 and 0.831 were obtained for RBFNN, GEP and MVNR models respectively, which confirmed that, the developed RBFNN model could be selected as a new model in piling technology. Definitely, other researchers and engineers can utilize the procedure and results of this study in order to get better design of driven piles.

Keywords: pile bearing capacity; radial basis function type artificial neural networks (RBFNN); multivariate nonlinear regression (MVNR); gene expression programming (GEP)

1. Introduction

A commonly-encountered problem in foundation design is the accurate prediction of the ultimate capacity of load bearing in case of each driven pile used in the project (Samui 2012, Samui and Kim 2013, Khari *et al*. 2019a, Momeni *et al*. 2020). It is true that in similar geotechnical conditions, the same bearing capacity equation is usually applied to various piles set up; however, this needs to be done very cautiously. Likewise, as the pile-soil interactions are not clear, most of the methods (already introduced in literature) fail to predict the pile capacity accurately (Meschke *et al*. 2013, Wu *et al*. 2019). Such failure can be due to simplifications and assumptions they normally take into account when interpreting behaviors of pile (Harandizadeh *et al*. 2018). The use of existing static solutions for the aim of determining the bottom resistance can

*Corresponding author, Senior Lecturer, E-mail: danialarmaghani@um.edu.my

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result in a similar convenience of different piles of a task. On the other hand, prevailing equations and methods of high efficiency normally take into account the over-simplification of the pile traveling problem (Samui 2008, Chen *et al*. 2019b). These methods mostly employ the information regarding pile and hammer in the prediction of the pile capacity. However, the soil characteristics are not considered in these methods. Lastly, despite the fact that static assessments are the most reliable strategy among all, they also suffer from limitations. For instance, in cases where the pile loading stops before failure of the pile, it will be difficult to interpret the test results. On the other hand, when loading is continued before failure of the pile, the check piles get impaired, and experiments can be applied to only a few piles. Add to the above-mentioned points the fact that such checks are very costly (Momeni *et al*. 2015a, Harandizadeh *et al*. 2019b). As a result, there is a need for a well-standardized technique capable of accurately estimating the compressive bearing capacity of each driven pile. Numerous parameters affect the calculation of bearing capacity of the piles; thus, efficient computational algorithms are necessary to effectively explore and control the interactions among the effective parameters. The techniques with no need for any prior assumption, e.g., artificial intelligence (AI) and machine learning (ML) techniques can provide solutions of a higher quality. Literature confirms the extensive application of AI and ML techniques such as genetic programming (GP), particle swarm optimization (PSO), adoptive neuro fuzzy inference system (ANFIS), gene expression programming (GEP) and artificial neural network (ANN) in civil engineering as well as geotechnical fields (Momeni *et al*. 2013, Najafzadeh and Azamathulla 2013, Najafzadeh *et al*. 2013, Toghroli *et al*. 2014, Yang *et al*. 2014, 2016, 2018, Najafzadeh 2015, Das and Suman 2015, Najafzadeh and Bonakdari 2016, Zhou *et al*. 2016, 2019, 2020a, 2020b, 2020c, Asteris *et al*. 2017, 2019, Kechagias *et al*. 2018, Koopialipoor *et al*. 2018, Wang *et al*. 2018, Bunawan *et al*. 2018, Apostolopoulou *et al*. 2019, Armaghani *et al*. 2019a, Hajihassani *et al*. 2019, Huang *et al*. 2019, Khari *et al*. 2019b, Armaghani *et al*. 2019b, Sarir *et al*. 2019, Xu *et al*. 2019a, 2019b, Armaghani *et al*. 2020a, Zhang *et al*. 2019, Chen *et al*. 2019a, Duan *et al*. 2020, Lu *et al*. 2020, Armaghani *et al*. 2020). In case of piling technology, a variety of input parameters have been considered by different scholars in modelling processes making attempt to estimate the bearing capacity of piles with a maximum level of accuracy (Momeni *et al*. 2014, 2015b, 2018, Armaghani *et al*. 2017).

Chan *et al*. (1995) employed a back-propagation neural network (BPNN) containing three layers in order to examine the driven piles bearing capacity with the help of the input parameters i.e., the elastic compression of soil and pile, pile setup, and generating energy used in a pile. They showed a successful use of BPNN technique in predicting pile bearing capacity. In another study of ANN, Lee and Lee (1996) used this technique for the purpose of estimating their experimental piles bearing capacity in addition to a number of full-level pile load tests extracted through a literature review. Their assumption was that the highest bearing capacities had suffered from some issues such as the ratio of penetration depth, the averaged regular penetration number close to the pile tip, the averaged regular penetration quantity along the pile shaft, pile arranged (last penetration depth/blow), as well as the hammer energy. Abu Kiefa (1998) attempted to propose a regression ANN capable of estimating a driven pile capacity within non-cohesive soil. He set four parameters as model inputs to his model, namely the soil friction angle, effective overburden pressure, duration of pile, and the cross-sectional region of the pile. Ardalan *et al*. (2009) made use of the group method of data handling (GMDH) model optimized by genetic algorithm (GA). Their input parameters were cone resistance and cone sleeve friction, and the pile shaft resistance. To this end, they utilized a data source containing 33 full-level pile loading lab tests accompanied with details of soil types and the cone penetration tests (CPTs), which were carried out nearby the location of the piles. In another study, Alkroosh and Nikraz (2012) developed a GEP equation for the prediction of the capacity of piles driven into cohesive soil. Their model utilized a number of independent variables such as the length and size of piles, weighted sleeve friction along the pile shaft, pile materials, and pile elastic modulus Data required for developing GEP model were gathered from the related literature involving a number of in-situ assessment of driven pile load and results obtained from the CPTs. Some other techniques e.g., PSO-ANN, GA-ANN, ICA-ANN, ANFIS-GMDH-PSO, and GP were introduced in the studies by Armaghani *et al.* (2017), Momeni *et al.* (2014), Moayedi and Armaghani (2018), Harandizadeh *et al.* (2019a), and Chen *et al.* (2019b), respectively, as the best predictive models of the pile ultimate capacity.

To effectively model the pile bearing capacity, the above-mentioned studies mainly made use of parameters such as pile setup, cone tip resistance, or N- standard penetration test (SPT) values. However, based on previous investigations, the number of hammer blows should be taken into consideration as the key parameter in the process of measuring the driven piles' ultimate bearing capacity. In this respect, the Flap number refers to the number of hammer blows used in order to drive into the soil the last one meter of remaining length of the pile. The value set for this case is a unique number for each one of the piles; it actually reflects the conditions of the soil and the way pile and soil interact with each other. Note that the Flap number greatly depends upon the type of hammer in use. As a result, the number of blows is multiplied by the hammer relative energy in a way to make a comparison on the level of blows each pile received.

In addition, in most of previously-conducted studies, it was assumed that the soil physical parameters do not work in a pile, whereas in the present study, not only the Flap hammer blows number, but also the soil parameters, geometric parameters of the piles, and the friction angle between pile and soil were taken into account as significant factors. To carry out a wide-ranging study, a dataset containing 100 piles (made from steel and concrete) was provided. Additionally, the information in regard to the soil conditions and the results obtained from field tests were considered as effective parameters on piling capacity. The data collected for the purpose of this study included various steel and concrete piles whose length was ranging from 15 m to 98 m.

In this study, initially, the method of radial basis function type neural networks (RBFNN) was employed to predict ultimate bearing capacity of the piles. Then, the GEP was used in a way to obtain an equation for predicting the capacity of pile from the Flap number and the other effective factors. At the final step, another method termed multivariate nonlinear regression (MVNR) was adopted for the estimation of pile capacity. The coefficient of determination (R^2) and root mean square error (RMSE) were used to test the precision level of the results obtained from each approach adopted. Then, the best predictive model among them was selected to predict pile bearing capacity.

2. Pile information and data used

For the purpose of this research, a database containing of 100 concrete and steel piles were taken into consideration. In each of them, information including the ground physical properties, the geometrical characteristics, static pile load test outputs, Flap number (the number of hammer strikes), and their particular hammer strike energies were gathered. The assumption was that factors such as the soil drained cohesion, friction angle of soil drained, and specific weight affect the conditions of soil. The two parameters of embedded duration and pile cross section refer to the pile geometric size and, on the other hand, the pile-soil friction position affects the pile material.

Table 1 Results of input and output used in the modeling (Milad *et al*. 2015)

Variable	Unit	Group	Min	Max	Mean
Average Cohesion (C)	kN/m^2	Input	0	148	32.4
Average Friction angle (ϕ)	Degree	Input	0	36.6	25.6
Average soil Specific weight (γ)	kN/m^3	Input	5.4	13.5	13.3
Pile-Soil friction angle (λ)	Degree	Input	10.1	17	13.7
Flap Number	-	Input	14	2291	495
Pile Area (A)	m^2	Input	0.07	1.6	0.4
Pile Length (L)	m	Input	14.2	98	27.11
Pile Capacity	kN	Output	540	52100	5133.1

In addition to all parameters selected, the Flap number was expected to be capable of representing all unknown factors that have effect in the process of measuring the bearing capacity of piles.

In the present paper, seven parameters were chosen to estimate the bearing capacity of piles, which are explained in the following:

A is cross section area of pile (m^2),

C is the drained soil cohesion (kN/m^2),

Flap Number (Hammer strikes = $Er \times N$) denoted as multiplication of relative energy of hammer (*Er)* and the number of hammers blows (*N)*;

γ is the effective soil specific weight (kN/m^3),

L is the embedded length of pile (m),

ϕ is friction angle of drained Soil (°) and λ is pile-soil interface friction angle (°).

At the time of measuring the input parameters, the following four issues were taken into consideration:

- The interpreted failure loads (capacities of the piles) that were employed as suggested by Eslami (1996). In case the failure load is not determined clearly, then 80% criterion proposed by Hansen (1963), was adopted.
- The average values that were recorded in case of the parameters transformed along with embedded size of the piles, which included the drained soil friction position, drained cohesion of the soil, specific weight of soil, and the spots where friction occurs between soil and piles.
- The effective specific excess weight that was taken into account as for elements of the soil that were positioned under the water table level (Bowles 1996).
- The results of the static load tests that could be found in performed computations (due to their acceptable level of precision). An assumption was that the period of time through which the test is prepared is lengthy enough for soil to be drained. As a result, in computations performed, the consolidated drained condition was also taken into account.

In addition, the values suggested by Bowles (1996) for lots of pile types and soil/rock were applied to various interface friction angles between soil and pile. As different hammer types were utilized to drive the piles, an attempt was made to have similar values for the hammer strike number. To this end, a normalization process was done on a number of hammer blows with the use of the hammer relative energy. In this respect, a Kobe 35 type hammer was chosen and considered to use in the process of measuring the relative energies (Tomlinson and Woodward 2007). Through the calculation performed, the Flap number was obtained through multiplying the hammer's relative energy and the number of blows (Prakash and Sharma 1990). Table 1 presents descriptions of all 100 input and output variables (Milad *et al*. 2015) used in the modeling process of this study.

3. Applied methods

3.1 Radial basis function type neural networks (RBFNN)

ANNs are common in the application of geotechnical research problems due to giving an interesting approach for modeling phenomenon's behavior. In recent years, different types of ANNs have been efficiently used to simulate different soil behaviors such as compaction of soil (Sinha and Wang 2008), soil liquefaction (Young-Su and Byung-Tak 2006), and thermal properties of soil (Erzin *et al*. 2008). They also utilized to the model arrangement of shallow fundamentals (Shahin *et al*. 2002), tension- stress behavior of sandy soil (Banimahd *et al*. 2005), and earth category fields (Kurup and Griffin 2006). Literature consists of numerous studies in which ANNs have been utilized aiming at determining the capacity of piles (Kiefa 1998; Alkroosh and Nikraz 2012). The method that was the first one applied to the prediction of the piles' bearing capacity with the use of their hammer strike and other effective factors was the Radial Basis Function Neural Network (RBFNN).

3.1.1 Architecture of RBF neural network

As depicted in Figure 1, RBFNN is a feedforward structure containing three layers. Among them, the input layer is responsible for distributing inputs to the hidden layer. In this hidden layer, each node denotes a radial function. The dimensionality of the node is similar to that of the input data. The calculation of the output is done by a linear combination. This combination is consisted of a weighted sum of the radial basis functions together with the bias, as expressed by Eq. (1)

$$y(x_i) = \sum_{j=1}^{k} w_j \, \phi(\left\| x_i - c_j \right\| + w_0 \tag{1}$$

In matrix notation

$$\begin{aligned} & y = \phi \times (w), \\ & w = \left[w_1 \, w_2 \ldots w_k \; w_0 \right],^T \\ & \phi = \begin{bmatrix} \phi_{11} & \phi_{21} & \cdots & \phi_{k1} & 1 \\ \phi_{12} & \phi_{23} & \cdots & \phi_{k2} & 1 \\ \phi_{13} & \phi_{23} & \cdots & \phi_{k3} & 1 \\ \vdots & \vdots & & \vdots & \vdots \\ \phi_{1m} & \phi_{2m} & \cdots & \phi_{km} & 1 \end{bmatrix} = \left[\phi_1 \;\; \phi_2 \;\; \phi_3 \; \ldots \phi_k \;\; 1 \right] \end{aligned} \tag{2}$$

3.1.2 RBFNs Nonlinear training algorithm

The parameters of the RBF network are listed as the spreads of the Gaussian RBF activation functions, centers of the RBF activation functions, and the weights from the hidden layer to the output one. In the nonlinear neural network, the gradient descent method is adopted in order to explore the centers, spread, and weights through the minimization of the cost function (mostly, the

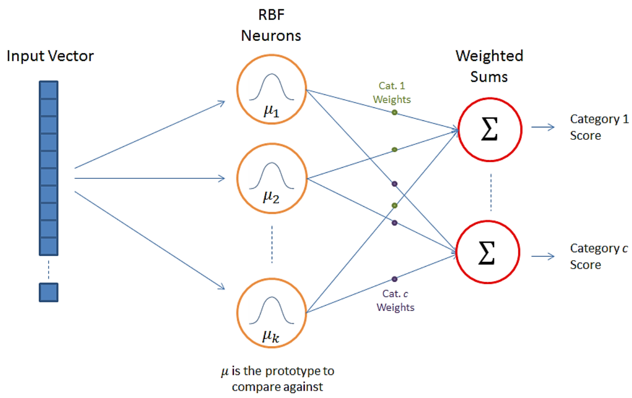


Fig. 1 RBF type neural network structure

squared error). The network parameters are adapted by the BP algorithm. This algorithm takes into consideration the cost function derivatives upon the parameters in an iterative process. The challenging issue is that the BP probably needs a number of iterations, and also this algorithm might be trapped in the cost function local minima (Asteris *et al*. 2016, 2019, 2020, Apostolopoulou *et al*. 2020, Armaghani *et al*. 2020b, Armaghani and Asteris 2020, Asteris, *et al*. 2020).

Divisions in Dataset Sampling

For the purpose of computations required, the samples were divided into two groups:

• Training set (70% Samples): The samples in this group were used to locate the neural system biases and weights in a way to reduce the error value as much as possible. Such samples are applied to the network in the course of the overall training. The error value obtained was used to adjust the system.

• Testing set (30% Samples): The samples in this group were applied to the assessment of the neural system with the best weights explored throughout the training process; the accuracy level was also measured in this course. Such samples do not affect the appropriate training; as a result, they can make available an unbiased way to evaluate the way the network performs both after and during the training process.

3.2 Gene Expression Programming (GEP)

3.2.1 GEP structural concepts

GEP is actually an extended version of the GA that is an evolutionary optimization algorithm works according to the genetics principles and natural selection theory. The evolutionary processing technique is GP that was introduced by (Koza 1992). This algorithm is applied to representing systematically the information provided through the manipulation and optimization of a network of computer models made up of terminals and functions in a way to be capable of searching for a model that can be best matched with the problem in hand. GP is defined as a domain-independent approach to solving problems. It creates computer programs involving a number of different terminals and features for the aim of solving the approximation problems through simulating the living organisms' biological evolutions and genetic operations that occur in

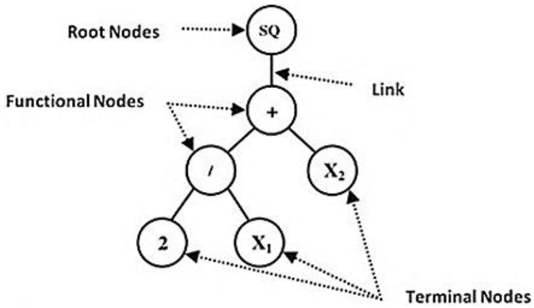


Fig. 2 Typical GEP tree representing function (Javadi *et al*. 2006)

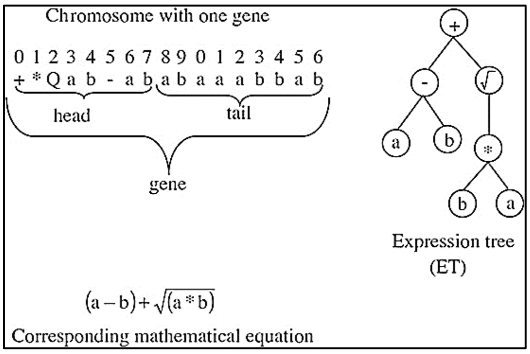


Fig. 3 ET of a chromosome with its relevant GEP equation (Kayadelen 2011)

nature. Standardized arithmetic processes (/, ×, +, −, sin, cos, log2, power, etc.) are the features and terminal that exist in the GP system. Furthermore, GP can be loaded with the Boolean logic features (And, Or, Not really, and so on), logical constants, numerical constants, mathematical features, in addition to user-defined operators (Sette and Boullart 2001). The selection of the features and terminals is done in a random way and they are formed collectively in a way to create a computer-based model with a root stage and branches that extend from each function and get close to each other in a terminal. Fig. 2 illustrates a proper instance of a GEP model in its tree representation shape (Javadi *et al*. 2006).

The process is started with the selection of units of terminals T and features F through a random way. For example, it is able to select the simple statistical operators F= {+, -, *, /} in order to form the features sets.

The terminals group is naturally consisted of independent variables of a specific problem, for instance, in case of those problems that contain two separate variables, x_1 and x_2 are $T=\{x_1, x_2\}$. A part of the step can be the selection of the architecture of chromosomes, i.e., gene numbers and the amount of linking features. Expression tree (ET) of a chromosome with its relevant GEP equation is depicted in Fig. 3.

3.3 Multivariate nonlinear regression approach

3.3.1 Non-linear regression & regression statistics concepts

Term of non-linear regression refers to a type of regression that is able to create a relationship

Table 2 Regression results of RBFNN method for various datasets in pile bearing capacity prediction

Data Division	Percentage of samples %	Correlation Coefficient (R)
All Dataset	100	0.92597
Training Dataset	70	0.99728
Testing Dataset	30	0.021034

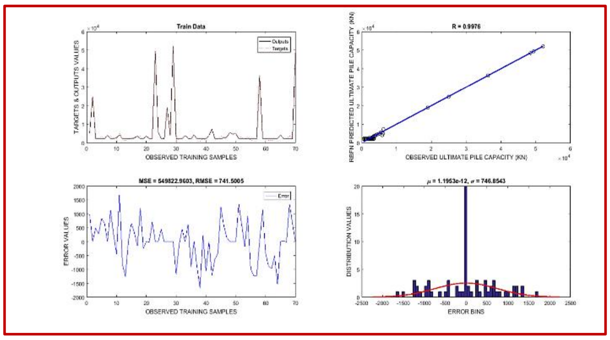


Fig. 4 Resulted charts for training datasets associated with fitting curve, R, MSE, RMSE a nd error histogram parameters

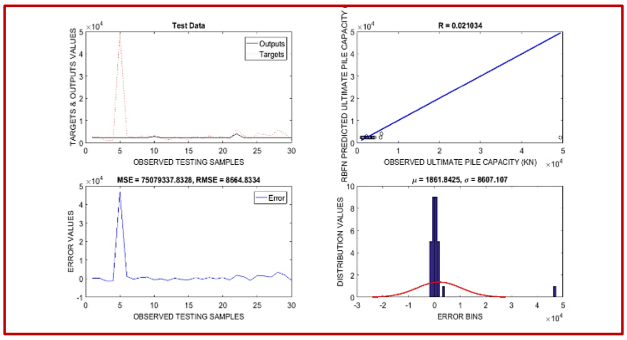


Fig. 5 Resulted charts for testing datasets associated with fitting curve, R, MSE, RMSE and error histogram parameters

between dependents and independent parameters. Data consisted of independent factors that are also known as explanatory variables (x) together with their response parameters (y). Typically, each y is demonstrated as a parameter with a mean distributed using a non-linear function $f(x, \beta)$.

For example, in case of the enzyme kinetics, the -MichaelisMenten model is as follows

$$v = \frac{V_{\max}[S]}{K_m + [S]} \tag{3}$$

Which can be written as

$$f(x,\beta) = \frac{\beta_1 x}{\beta_2 + x} \tag{4}$$

where β_1 stands for the parameter $V_{\max}$, β_2 denotes the parameter K_m, and [S] signifies the independent variable (x). The nonlinearity of this function is clear since it cannot be articulated as a linear combination of the two β_s. Some other types of non-linear functions are logarithmic functions, exponential functions, Gaussian function, power features, Lorenz curves, and trigonometric features. Unlike the linear regression, many regional minima of function can appear to be optimized, and the global minimum quantity can lead to the formation of a biased estimation. The predicted values of parameters are applied to optimization algorithms in order to explore the least sum of squares.

The assumption underlying this process is that a linear function could approximate the model as following

$$f(x_i, \beta) \approx f^0 + \sum_j J_{ij}\beta_j \tag{5}$$

where $J_{ij} = \dfrac{\partial f(x_i, \beta)}{\partial \beta_j}$. It follows from this that the least squares estimators are given by

$$\hat{\beta} \approx (J^T J)^{-1} J^T y \tag{6}$$

Non-linear regression statistics are computed and employed similar to those in the linear regression statistics; however, in formulas adopted in this process, J is used in place of X. Linear approximation introduces bias to the statistics. As a result, it is needed to be very cautious in the interpretation of the statistics generated from nonlinear models.

4. Results and discussions

4.1 Results of RBFNN application in predicting pile bearing capacity

In case of the neural system, the MATLAB software chooses 70% of the total datasets for the training purposes in an automatic and appropriate way. The remaining 30% of the datasets were dedicated to testing purposes. These samples are also chosen in a random way. To attain the RBF network outcomes, the seven effective input parameters need to be ordered as offered in the following column matrix:

$$Input\ \ Matrix = [C \quad \phi \quad \gamma \quad \lambda \quad Flap \quad A \quad L]'$$

In the term of "a=$f(wp+b)$", p refers to the input matrix, b, and w present bias and weight matrices, respectively, the results of RBF can be calculated from the first layer to the last one. In this way, the bearing capacity of the pile can be calculated using the RBFN technique.

The correlation coefficient, i.e., the regression determination coefficient, which is signified by R, was applied to the measurement of the success rate of the RBF type neural network regarding the prediction of the piles' capacity. The coefficient reveals the variation percentage within the datasets; the obtained value ranges from 0 to 1. When the value of R is closer to 1, this means the model is well-matched with the data; on the other hand, when this value is closer to 0, it means the model is not matched well with the data perfectly. Table 2 shows these values for all three datasets (all samples, training samples, test samples). Assessment of RBF neural network predicted outputs and actual pile bearing capacity has been showed in Figs. 4 and 5, respectively for training and testing stages. In addition, mean square error (MSE) and RMSE were applied to verifying the general performance of the network (Figs. 4 and 5). Lower MSE and RMSE values indicate a much better response. The differences in R values between training and test datasets indicated that RBFN could not fit and predict desired outputs within the test datasets since there was not provided adequate test datasets to network and others reason for this issue is related to the trend of scattering points in multi-dimensional space.

4.2 Results of GEP application in predicting pile bearing capacity

In the present study, GEP was used as the second predictive technique for evaluating the bearing capacity of driven piles. For developing this approach, GeneXproTools package were utilized for modelling GEP algorithm for simplicity purpose (please refer to reference link, https://www.gepsoft.com/, for more details on how to setup software and perform analysis); briefly discussed in GEP algorithm, terminal is responsible for identifying the independent variables that are applied to the approximation of the dependent variables. In the analysis performed in this study, terminal recognizes seven independent variables; one of them predicts the pile capacity that is the dependent variable. After that, a fitness function is assigned to be applied for evaluation process. GEP continues its operation until the predefined termination criterion (max limit of generation) is met. Once the fitness is varied in a narrow range, GEP can stop its operation. The established mathematical function, is consisted of {/, ×, +, −, log}. A lexicographic parsimony pressure (lexica tour) process of the reproducing within GEP assessment was applied to the selection of the parents as the technique settings bloat. The values set for the maximum generation and population size for this evaluation process was 78901 and 250, respectively. In addition, the maximum tree depth was fixed as 26. The stopping criterion can be also the achievement of the maximum generation value or the maximum fitness function. The evaluation on the effects was done when 41 computer runs completed. The best individual achieved in the operated runs was reserved and the conforming parse tree was attained.

The greatest tree was changed into a conforming mathematical method in order to obtain the next equation. This equation makes use of only the friction angle of soil, hammer strike, length of pile, the friction angle between pile and soil, specific weight of soil, and size of pile as the independent variables in order to make predictions about the dependent variable, i.e., the bearing capacity of pile. Users have option to define a number of setting parameters (see Table 3) or change them while algorithm is working.

The final formula proposed by GEP was evaluated through taking into account all 100 piles' dataset. The actual values of bearing capacity of piles were compared to those that have been derived by the regression equation. The selection of the S-expression (a symbolic expression) was based on the lowest fitness values indicating the minimum error among their measured and estimated data. Lower fitness value indicates a model of a higher quality performance.

R^2 and RMSE indices were applied to verify the power of GEP in predicting pile bearing capacity. Figures 6-9 demonstrate a schematically comparison between the measured bearing capacity values and predicted outputs derived by generated regression model Eq. (2) for the training dataset. The R^2 and RMSE values in training datasets correspond to 0.947 and 766.168 respectively assigned to generated model (Model 431) in training stage, and also R^2 and RMSE values within testing dataset which assigned to generated model (Model 447) are 0.964 and 2991.179 respectively.

Figs. 6-9 illustrate to provide the graphical representation of tabulated results as already mentioned above to show the best-fitted generated model performance and comparing between

Table 3 The user-defined parameters and statistical variations of errors during performing GEP software

Statistics - Training	Statistics - Testing
General	General
Best Fitness:1.30349608618885	Best Fitness:0.334204632485045
Max Fitness:1000	Max Fitness:1000
R-square:0.94666823012815	R-square:0.963905411023848
Additional Information	Additional Information
Correlation Coefficient (CC):0.97296877140438	Correlation Coefficient (CC):0.98178684602302
Mean Squared Error (MSE):587000	Mean Squared Error (MSE):8950000
Root Mean Squared Error(RMSE):766.167627578991	Root Mean Squared Error (RMSE):2991.1787515759
Relative Absolute Error (RAE):0.34301901398373	Relative Absolute Error (RAE):0.16257739612448
Mean Absolute Error (MAE):599.905640261895	Mean Absolute Error (MAE):1655.052821601
Relative Squared Error (RSE):0.05354337387778	Relative Squared Error (RSE):0.0409446606928
Root Relative Squared Error (RRSE):0.23139441194155	Root Relative Squared Error (RRSE): 0.20234787049239
Data	
Independent Variables:7 Training Records:67 Testing Records:33 Program Size:41 Chromosomes:30 Genes:3 Head Size:8 Tail Size:9 Dc Size:9 Gene Size:26 Linking Function:Addition	

Table 4 Summary of statistics results associated with fitness parameters and R2 values corres ponding to the best fitted generated model derived by GEP method

Summary Statistics:		
	Training	Testing
Best Fitness	Model 447: 1.303	Model 447: 0.334
Best R^2	Model 431: 0.947	Model 447: 0.964
Average Fitness	0.977	7.48E-04
Average R^2	0.860	0.002

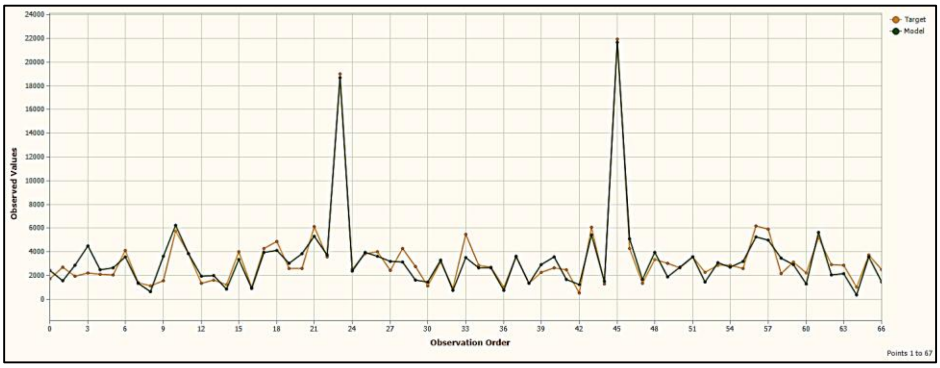


Fig. 6 Fitted-curve plot over train datasets in training stage for GEP model

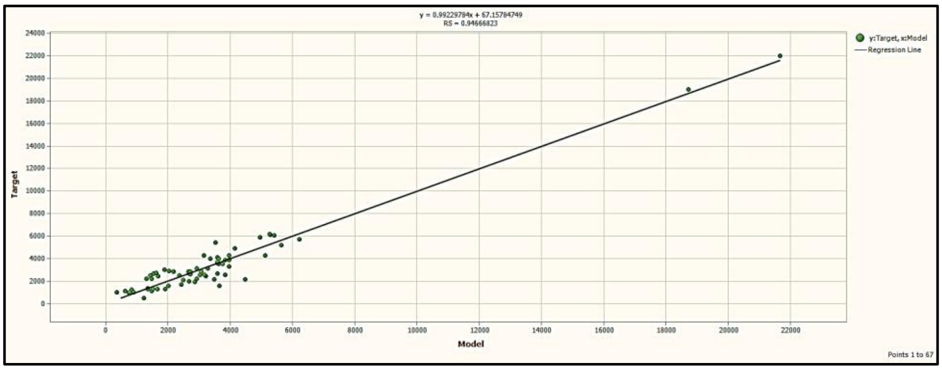


Fig. 7 Regression plot between measured (target) and predicted values (model output) in training stage for GEP model

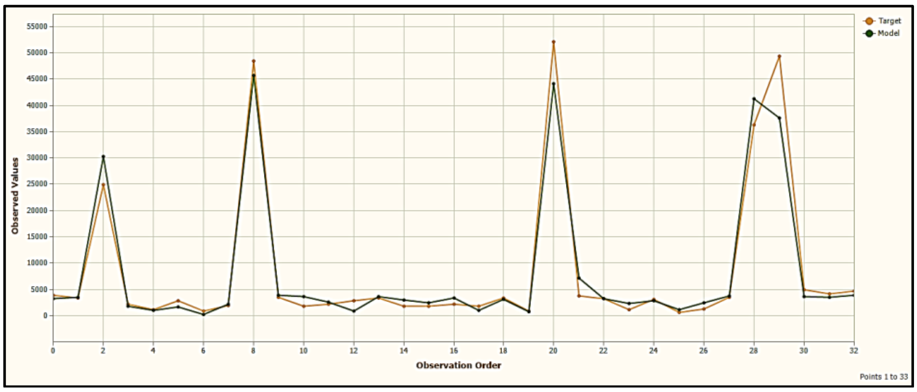


Fig. 8 Fitted-curve plot over test datasets in testing stage for GEP model

training and testing datasets for better understanding the behavior of model produced by GEP technique.

As shown in Table 4, statistics indices results related to fitness, coefficient correlation values, and also best-fitted generated model (Model 447) tabulated for making purposes comparison as below.

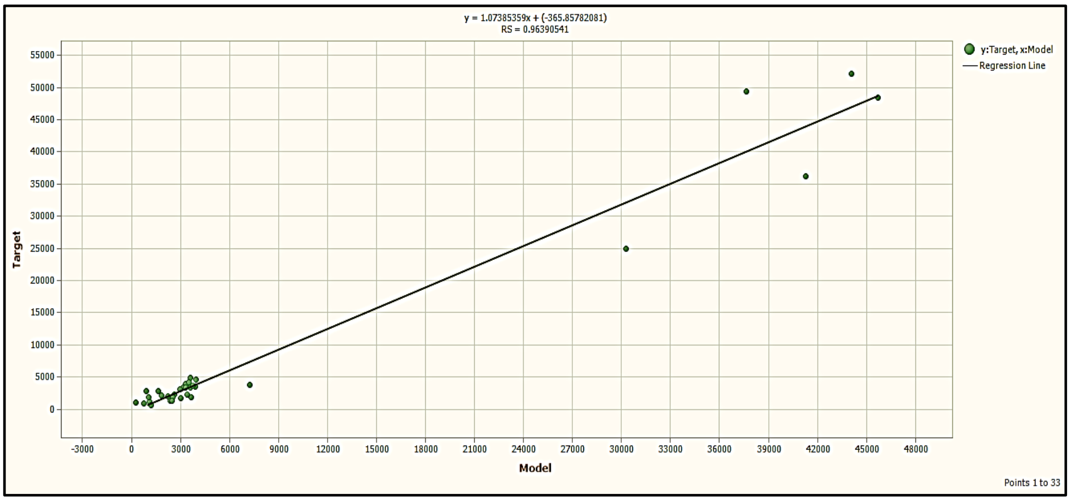


Fig. 9 Regression plot between measured (target) and predicted values (model output) in testing stage for GEP model

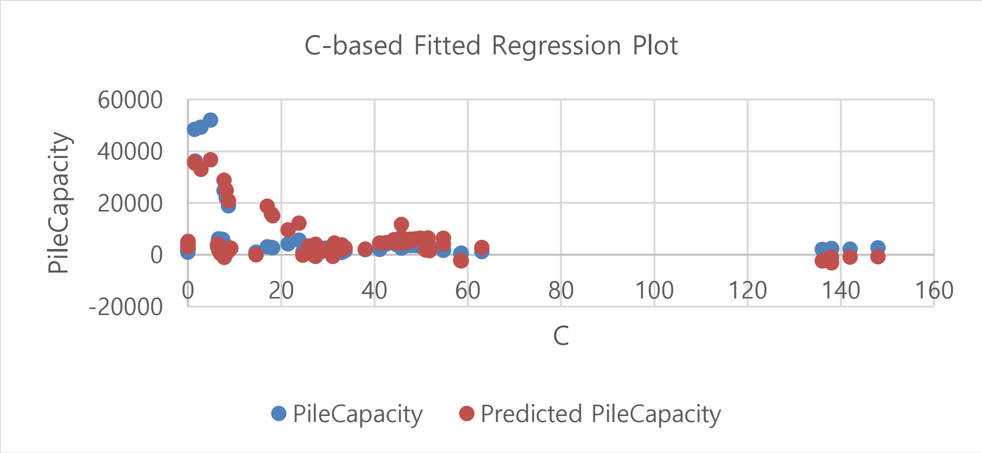
4.3 Results of MVNR application in pile bearing capacity prediction

In this study, Excel and MATLAB software were utilized for performing the MVNR analysis to predict the pile bearing capacity from seven independent input variables (C, Phi, Gamma, Lambda, Flap Number, Area and Length) which yielded the following nonlinear Eq. (7) as a nonlinear model function (polynomial function) describing all effective parameters defined by a researcher in this study based on some trial and error process to fit the scatter data trend.

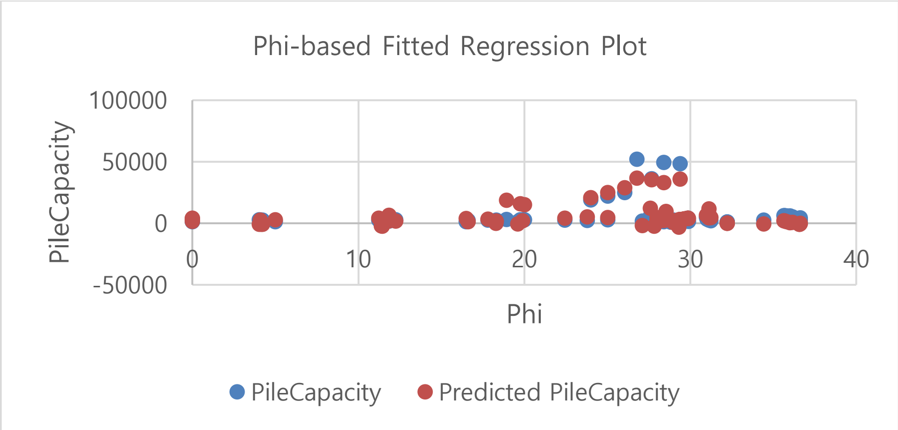
$$\begin{aligned} y &= B_2 \times x_1 + B_3 \times x_2 + B_4 \times x_3 + B_5 \times x_4 + B_6 \times x_5 + B_7 \times x_6 \wedge B_5 + x_7 \wedge B_6 \\ y &= -24.55C - 17.43Phi + 547.04Gamma - 775.77Landa - 0.41Hammer + 2854.38Area^{-775.77} + Length^{-0.41} \end{aligned} \tag{7}$$

Figs. 10(a) to 10(g) indicate the measured pile capacities (observations) individually for each independent variable using derived MVNR Eq. (7). The overall equation performance has been evaluated using all datasets (100 data). To compare other applied methods in this research, we utilized R^2 and standard error to verify the accuracy of the pile capacity output (predicted dependent variable) which experienced the values of R^2=0.831 and standard error=4506.92, respectively.

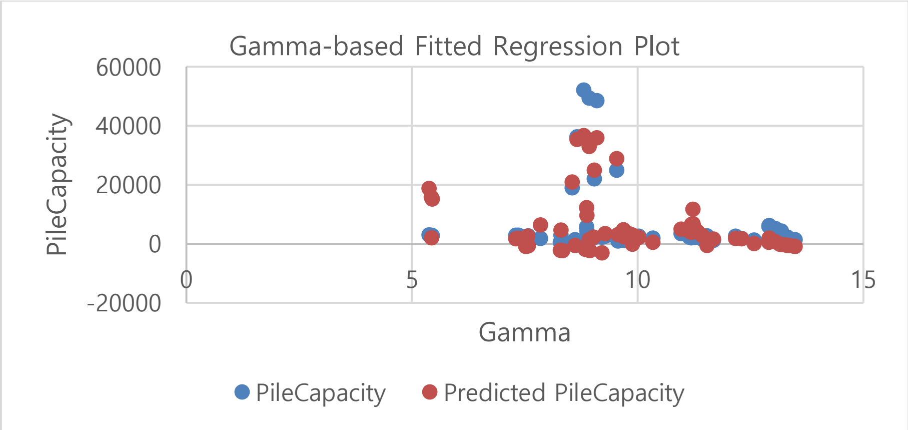
To examine the way the major parameters, affect the ultimate capacity of pile, the required analyses were performed with the use of almost all effective parameters. Then, an evaluation of variance (ANOVA) was carried out in order to identify the statistically-important parameters that have impact upon the capacity of pile. In general, ANOVA carries out a one-way, well-balanced assessment to do an evaluation on the methods containing a number of columns of datasets, each of which denotes an unbiased sample that is created through mutually independent observations. The testing conducted on the regression significance is for determining whether there is a nonlinear/linear relation between variable responses and the set of predictor variables. The p-value is returned by the function beneath the null hypothesis in which the samples are drawn from populations with similar mean. In Fig. 11, the error histogram (residuals) is displayed to better visualize the error distribution in the approach of regression analysis.



(a) Regression plot of measured vs. predicted pile bearing capacity for drained soil cohesion (C) variable

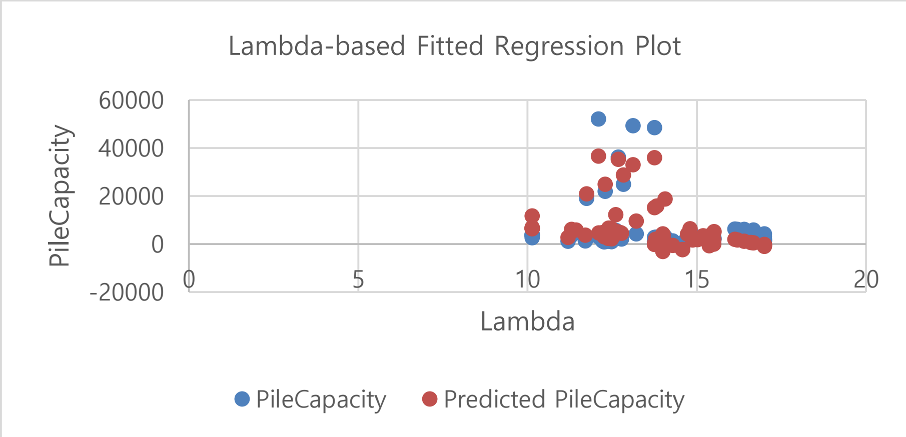


(b) Regression plot of measured vs. predicted pile bearing capacity for drained soil friction angle (Phi) variable

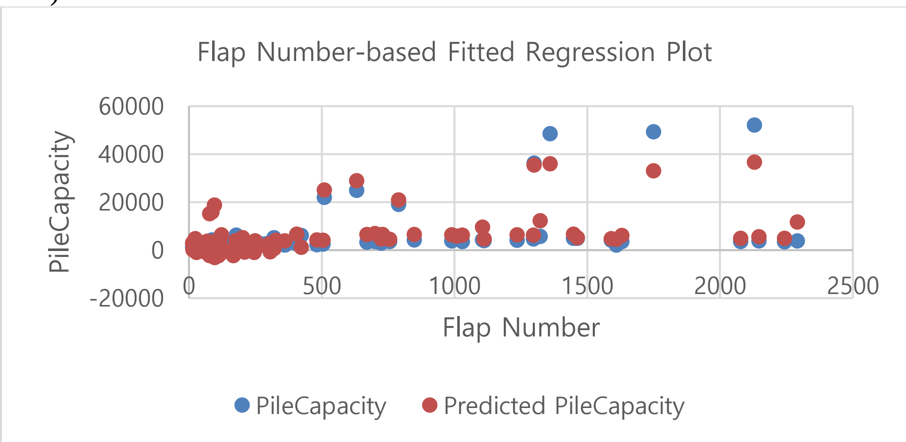


(c) Regression plot of measured vs. predicted pile bearing capacity for effective soil specific weight (Gamma) variablet

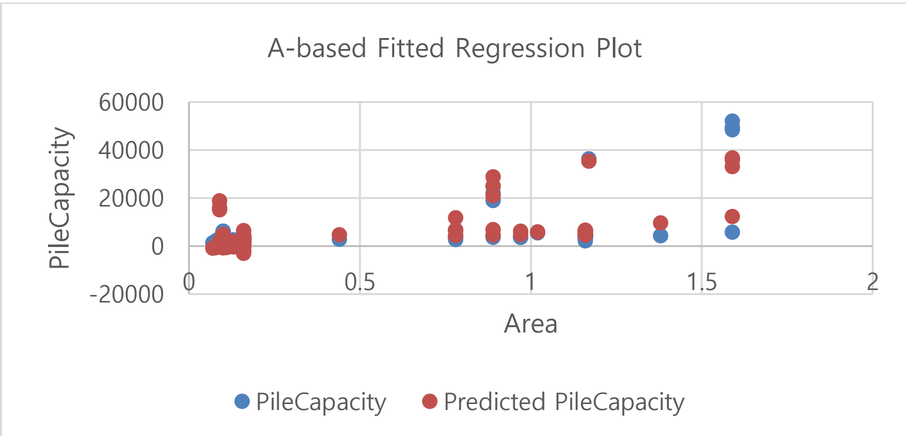
Fig. 10 Continued



(d) Regression plot of measured vs. predicted pile bearing capacity for pile-soil interface friction angle (Lambda) variable

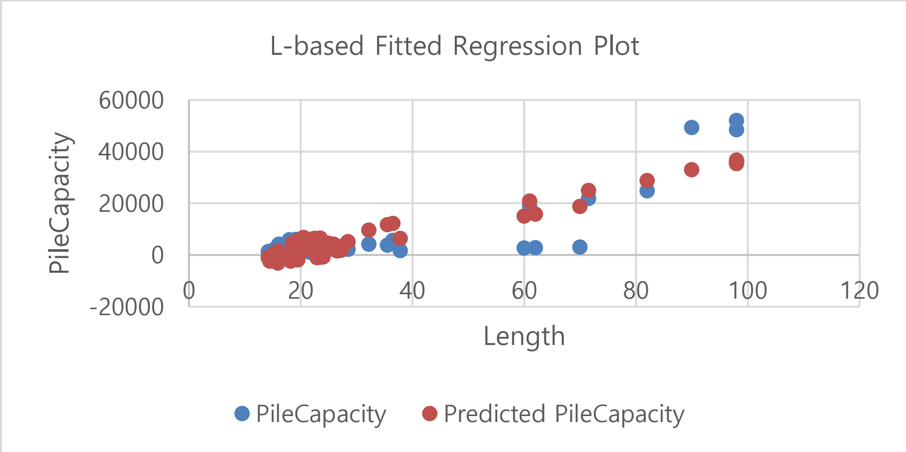


(e) Regression plot of measured vs. predicted pile bearing capacity for hammer strikes (Flap Number) variable



(f) Regression plot of measured vs. predicted pile bearing capacity for pile cross section area (A) variable

Fig. 10 Continued



(g) Regression plot of measured vs. predicted pile bearing capacity for embedded pile length (L) variable

Fig. 10

Table 5 Results obtained by RBFNN, GEP and MVNR

Predictive Technique	RMSE	R^2
RBFNN	741	0.9976
GEP	766.16	0.9466
MVNR	4506.92	0.831

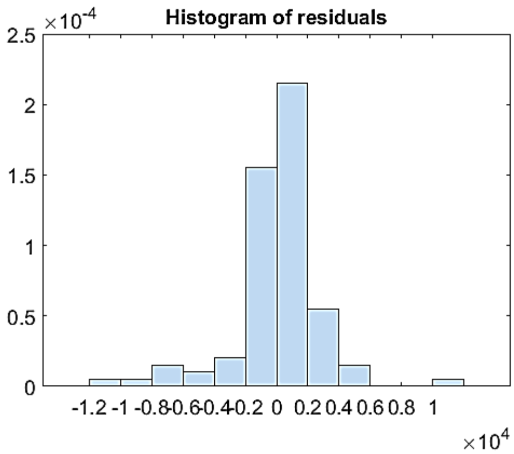


Fig. 11 Histogram of error distribution statistic chart

5. Assessment of the applied methods

The R^2 and RMSE values obtained from all methods considered are presented in Table 5 for comparison purposes. As shown in the table, the RBF neural network offered an appropriate solution overall, and the MVNR obtained unexpectedly less accurate results compared to the Gene

Expression Programming method that offered better results.

As can be seen in Table 5, amongst all considered methods, the RBF neural network showed relatively a satisfactory overall performance regarding the estimation of ultimate capacity of piles with the minimum RMSE value (741) and maximum R^2 value (0.9976) in comparison with the MVNR and GEP in training stage. Amongst the formulas derived in this study, the fitted nonlinear regression model that applied parameters of high level of effectiveness like the pile cross-sectional area, hammer strike, and pile size, etc. showed a performance of the lowest quality; it had the maximum value of standard error (4506.92) and minimum R^2 (0.831). The results of this study showed that although neural networks are considered as black box analyzer in prediction purposes, they are able to provide a wonderful level of accuracy and the lowest level of system errors.

5. Conclusions

In the present study, an innovative approach was introduced according to the No. of hammer strikes termed Flap Number and the other parameters that were effective on the prediction of the load bearing capacity of driven piles. Hence, three predictive approaches i.e., RBFNN, MVNR, and GEP were employed for the purpose of estimating the ultimate loading bearing capacity of piles with taking into consideration all effective parameters. In the initial part which was conducted and proposed with the use of the RBFNN to estimate capacity of pile. In another section of this study, the GEP was used to attain a predictive equation of the bearing capacity of the piles. Then, the MVNR was employed for the aim of predicting the relationships between pile capacity and other effective independent parameters separately for each independent variable.

According to findings of this research, the methods introduced here established a programmatic and reliable alternative soft computing methods that can be used effectively to predict the axial pile capacity without any need for conducting experimental methods that are both time consuming and costly. The accuracy level of the estimated values for pile capacity in case of each one of the methods considered here was assessed with the use of RMSE and R^2. Among all developed models, the RBFNN returned the most proper results with minimum RMSE (741). From among the formulas attained for the estimation of ultimate capacity of piles, the fitted MVNR model performed with the lowest accuracy level (R^2=0.831 and standard error=4506.92). The hammer strike can represent the interaction between soil and pile; as a result, it can be used as a significant parameter for the estimation of the bearing capacity of driven piles. To apply this parameter, the impact of numerous hammer strikes upon the friction fatigue progress along the pile shaft in the course of driving the piles must be taken into account. Although the capacity of pile was utilized as the consequence of the employed systems, more investigations are required to identify the effects of the Flap number on the pile capacity.

References

Alkroosh, I. and Nikraz, H. (2012), “Predicting axial capacity of driven piles in cohesive soils using intelligent computing”, *Eng. Appl. Artif. Intel*. **25**, 618-627. https://doi.org/10.1016/j.engappai.2011.08.009

Apostolopoulou, M., Armaghani, D.J., Bakolas, A., Douvika, M.G., Moropoulou, A. and Asteris, P.G. (2019), “Compressive strength of natural hydraulic lime mortars using soft computing techniques”, *Procedia*

Struct. Integr. **17**, 914-923. https://doi.org/10.1016/j.prostr.2019.08.122.

Apostolopoulou, M., Armaghani, D.J., Bakolas, A., Douvika, M.G., Moropoulou, A. and Asteris, P.G. (2020), "Mapping and holistic design of natural hydraulic lime mortars", *Cement Concrete Res*., **136**, 106167. https://doi.org/10.1016/j.cemconres.2020.106167.

Ardalan, H., Eslami, A. and Nariman-Zadeh, N. (2009), "Piles shaft capacity from CPT and CPTu data by polynomial neural networks and genetic algorithms", *Comput. Geotech*. **36**, 616-625. https://doi.org/10.1016/j.compgeo.2008.09.003.

Armaghani, D.J. and Asteris, P.G. (2020), "A comparative study of ANN and ANFIS models for the prediction of cement-based mortar materials compressive strength", *Neural. Comput. Appl*. 1-32. https://doi.org/10.1007/s00521-020-05244-4

Armaghani, D.J., Asteris, P.G., Fatemi, S.A., Hasanipanah, M., Tarinejad, R., Rashid, A.S.A. and Huynh, V. V. (2020a), "On the use of neuro-swarm system to forecast the pile settlement", *Appl. Sci*., **10**, 1904. https://doi.org/10.3390/app10061904.

Armaghani, D.J., Hatzigeorgiou, G.D., Karamani, C., Skentou, A., Zoumpoulaki, I. and Asteris, P.G. (2019a), "Soft computing-based techniques for concrete beams shear strength", *Procedia Struct. Integr*. **17**, 924-933. https://doi.org/10.1016/j.prostr.2019.08.123.

Armaghani, D.J., Koopialipoor, M., Marto, A. and Yagiz, S. (2019b), "Application of several optimization techniques for estimating TBM advance rate in granitic rocks", *J. Rock Mech. Geotech. Eng*. https://doi.org/10.1016/j.jrmge.2019.01.002.

Armaghani, D.J., Mirzaei, F., Shariati, M., Trung, N.T., Shariati, M. and Trnavac, D. (2020b), "Hybrid ANN-based techniques in predicting cohesion of sandy-soil combined with fiber", *Geomech. Eng*., **20**, 191-205. http://dx.doi.org/10.12989/gae.2020.20.3.191.

Armaghani, D.J., Momeni, E. and Asteris, P. (2020), "Application of group method of data handling technique in assessing deformation of rock mass", *Metaheuristic Comput. Appl*., **1**(1), 1-18. http://dx.doi.org/10.12989/mca.2020.1.1.001.

Armaghani, D.J., Raja, R.S.N.S.B., Faizi, K. and Rashid, A.S.A. ((2017), "Developing a hybrid PSO–ANN model for estimating the ultimate bearing capacity of rock-socketed piles", *Neural. Comput. Appl*., **28**, 391-405. https://doi.org/10.1007/s00521-015-2072-z.

Asteris, P, Roussis, P. and Douvika, M. (2017), "Feed-forward neural network prediction of the mechanical properties of sandcrete materials", *Sensors*. **17**, 1344. https://doi.org/10.3390/s17061344.

Asteris, P.G., Apostolopoulou, M., Armaghani, D.J., Cavaleri, L., Chountalas, A.T., Guney, D. and Kotsonis, E. (2020), "On the metaheuristic models for the prediction of cement-metakaolin mortars compressive strength", *Metaheuristic Comput. Appl*., **1**(1), 63-99. http://dx.doi.org/10.12989/mca.2020.1.1.063.

Asteris, P.G., Apostolopoulou, M., Skentou, A.D. and Moropoulou, A. (2019), "Application of artificial neural networks for the prediction of the compressive strength of cement-based mortars", *Comput. Concrete*, **24**, 329-345. https://doi.org/10.12989/cac.2019.24.4.329.

Asteris, P.G., Douvika, M.G., Karamani, C.A., Skentou, A.D., Chlichlia, K., Cavaleri, L. and Zaoutis, T.E. (2020), "A novel heuristic algorithm for the modeling and risk assessment of the covid-19 pandemic phenomenon", *Comput. Model. Eng. Sci*., **125**(2), 1-14. https://doi.org/10.32604/cmes.2020.013280.

Asteris, P.G., Kolovos, K.G., Douvika, M.G. and Roinos, K. (2016), "Prediction of self-compacting concrete strength using artificial neural networks", *Eur. J. Environ. Civ. Eng*. **20**(sup1), s102-s122. https://doi.org/10.1080/19648189.2016.1246693.

Banimahd, M., Yasrobi, S.S. and Woodward, P.K. (2005), "Artificial neural network for stress–strain behavior of sandy soils: Knowledge based verification", *Comput. Geotech*., **32**, 377-386. https://doi.org/10.1016/j.compgeo.2005.06.002.

Bowles, L.E. (1996), *Foundation analysis and design*. McGraw-hill.

Bunawan, A.R., Momeni, E., Armaghani, D.J. and Rashid, A.S.A. (2018), "Experimental and intelligent techniques to estimate bearing capacity of cohesive soft soils reinforced with soil-cement columns", *Measurement*, **124**, 529-538. https://doi.org/10.1016/j.measurement.2018.04.057.

Chan, W.T., Chow, Y.K. and Liu, L.F. (1995), "Neural network: an alternative to pile driving formulas", Comput. Geotech. **17**, 135-156. https://doi.org/10.1016/0266-352X(95)93866-H.

Chen, H., Asteris, P.G., Jahed Armaghani, D., Gordan, B. and Pham, B.T. (2019a), "Assessing dynamic conditions of the retaining wall: Developing two hybrid intelligent models.", *Appl. Sci*., **9**, 1042. https://doi.org/10.3390/app9061042.

Chen, W., Sarir, P., Bui, X.N., Nguyen, H., Tahir, M.M. and Armaghani, D.J. (2019b), "Neuro-genetic, neuro-imperialism and genetic programing models in predicting ultimate bearing capacity of pile", *Eng. Comput*., https://doi.org/10.1007/s00366-019-00752-x.

Das, S.K. and Suman, S. (2015), "Prediction of lateral load capacity of pile in clay using multivariate adaptive regression spline and functional network", *Arab. J. Sci. Eng*., **40**, 1565-1578. https://doi.org/10.1007/s13369-015-1624-y.

Duan, J., Asteris, P.G., Nguyen, H., Bui, X.N. and Moayedi, H. (2020), "A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model", *Eng. Comput*. https://doi.org/10.1007/s00366-020-01003-0.

Erzin, Y., Rao, B.H. and Singh, D.N. (2008), "Artificial neural network models for predicting soil thermal resistivity", *Int. J. Therm. Sci*., **47**, 1347-1358. https://doi.org/10.1016/j.ijthermalsci.2007.11.001.

Eslami, A. (1996), *Bearing capacity of piles from cone penetration data.*

Hajihassani, M., Abdullah, S.S., Asteris, P.G. and Armaghani, D.J. (2019), "A gene expression programming model for predicting tunnel convergence", *Appl. Sci*., **9**, 4650. https://doi.org/10.3390/app9214650.

Hansen, J.B. (1963), "Discussion on hyperbolic stress-strain response: Cohesive soils", *J. Soil Mech. Found. Eng*., **89**(4), 241-242

Harandizadeh, H., Armaghani, D.J. and Khari, M. (2019a), "A new development of ANFIS–GMDH optimized by PSO to predict pile bearing capacity based on experimental datasets", *Eng. Comput*. 1-16. https://doi.org/10.1007/s00366-019-00849-3

Harandizadeh, H., Toufigh, M.M. and Toufigh, V. (2018), "Different neural networks and modal tree method for predicting ultimate bearing capacity of piles", *Iran Univ. Sci. Technol*., **8**, 311-328. http://ijoce.iust.ac.ir/article-1-347-en.html.

Harandizadeh, H., Toufigh, M.M. and Toufigh, V. (2019b), "Application of improved ANFIS approaches to estimate bearing capacity of piles", *Soft Comput*., **23**(19), 9537-9549. https://doi.org/10.1007/s00500-018-3517-y.

Huang, L., Asteris, P.G., Koopialipoor, M., Armaghani, D.J. and Tahir, M.M. (2019), "Invasive weed optimization technique-based ANN to the prediction of rock tensile strength", *Appl. Sci*., **9**(24), 5372. https://doi.org/10.3390/app9245372.

Javadi, A.A., Rezania, M. and Nezhad, M.M. (2006), "Evaluation of liquefaction induced lateral displacements using genetic programming", *Comput. Geotech*., **33**, 222-233. https://doi.org/10.1016/j.compgeo.2006.05.001.

Kayadelen, C. (2011), "Soil liquefaction modeling by genetic expression programming and neuro-fuzzy", *Expert Syst. Appl*., **38**(4), 4080-4087. https://doi.org/10.1016/j.eswa.2010.09.071.

Kechagias, J., Tsiolikas, A., Asteris, P. and Vaxevanidis, N. (2018), "Optimizing ANN performance using DOE: application on turning of a titanium alloy", In: MATEC Web of Conferences. EDP Sciences.

Khari, M., Armaghani, D.J. and Dehghanbanadaki, A. (2019a), "Prediction of lateral deflection of small-scale piles using hybrid PSO–ANN model.", 1-11. *Arab. J. Sci. Eng*., https://doi.org/10.1007/s13369-019-04134-9

Khari, M., Dehghanbandaki, A., Motamedi, S. and Armaghani, D.J. (2019b), "Computational estimation of lateral pile displacement in layered sand using experimental data", *Measurement*, **146**, 110-118. https://doi.org/10.1016/j.measurement.2019.04.081.

Kiefa, M.A.A. (1998), "General regression neural networks for driven piles in cohesionless soils", *J. Geotech. Geoenvironm. Eng*., **124**(12), 1177-1185. https://doi.org/10.1061/(ASCE)1090-0241(1998)124:12(1177).

Koopialipoor, M., Nikouei, S.S., Marto, A., Fahimifar, A., Armaghani, D.J. and Mohamad, E.T. (2018), "Predicting tunnel boring machine performance through a new model based on the group method of data handling", *Bull. Eng. Geol. Environ*. **78**, 3799-3813. https://doi.org/10.1007/s10064-018-1349-8.

Koza, J.R. (1992), *Genetic programming II. automatic discovery of reusable subprograms*, MIT Press,

Cambridge, M.A.
Kurup, P.U. and Griffin, E.P. (2006), "Prediction of soil composition from CPT data using general regression neural network", *J. Comput. Civil Eng.*, **20**, 281-289. https://doi.org/10.1061/(ASCE)0887-3801(2006)20:4(281).
Lee, I.M. and Lee, J.H. (1996), "Prediction of pile bearing capacity using artificial neural networks", *Comput. Geotech.*, **18**, 189-200. https://doi.org/10.1016/0266-352X(95)00027-8.
Lu, S., Koopialipoor, M., Asteris, P.G., Bahri, M. and Armaghani, D.J. (2020), "A novel feature selection approach based on tree models for evaluating the punching shear capacity of steel fiber-reinforced concrete flat slabs", *Materials (Basel).* **13**, 3902. https://doi.org/10.3390/ma13173902.
Meschke, G., Ninić, J., Stascheit, J. and Alsahly, A. (2013), "Parallelized computational modeling of pile-soil interactions in mechanized tunneling", *Eng. Struct.*, **47**, 35-44. https://doi.org/10.1016/j.engstruct.2012.07.001.
Milad, F., Kamal, T., Nader, H. and Erman, O.E. (2015), "New method for predicting the ultimate bearing capacity of driven piles by using Flap number", *KSCE J. Civil Eng.*, **19**, 611-620. https://doi.org/10.1007/s12205-013-0315-z.
Moayedi, H. and Armaghani, D.J. (2018), "Optimizing an ANN model with ICA for estimating bearing capacity of driven pile in cohesionless soil", *Eng. Comput.*, **34**, 347-356. https://doi.org/10.1007/s00366-017-0545-7.
Momeni, E. Armaghani, D.J. Fatemi, S.A. and Nazir, R. (2018), "Prediction of bearing capacity of thin-walled foundation: a simulation approach", *Eng. Comput.*, **34**, 319-327. https://doi.org/10.1007/s00366-017-0542-x.
Momeni, E., Dowlatshahi, M.B., Omidinasab, F., Maizir, H. and Armaghani, D.J. (2020), "Gaussian process regression technique to estimate the pile bearing capacity", *Arab. J. Sci. Eng.*, https://doi.org/10.1007/s13369-020-04683-4.
Momeni, E., Maizir, H., Gofar, N. and Nazir, R. (2013), "Comparative study on prediction of axial bearing capacity of driven piles in granular materials", *J. Teknol.*, **61**(3), 15-20.
Momeni, E., Nazir, R., Armaghani, D.J. and Maizir, H. (2014), "Prediction of pile bearing capacity using a hybrid genetic algorithm-based ANN", *Measurement*, **57**, 122-131. https://doi.org/10.1016/j.measurement.2014.08.007.
Momeni, E., Nazir, R., Armaghani, D.J. and Maizir, H. (2015a), "Application of artificial neural network for predicting shaft and tip resistances of concrete piles", *Earth Sci. Res. J.*, **19**, 85-93. http://dx.doi.org/10.15446/esrj.v19n1.38712.
Momeni, E., Nazir, R., Armaghani, D.J. and Sohaie, H. (2015b), "Bearing capacity of precast thin-walled foundation in sand", *Proc. Institution Civil Eng. Geotech. Eng.*, **168**, 539-550. https://doi.org/10.1680/jgeen.14.00177.
Najafzadeh, M. (2015), "Neuro-fuzzy GMDH systems based evolutionary algorithms to predict scour pile groups in clear water conditions", *Ocean Eng.*, **99**, 85-94. https://doi.org/10.1016/j.oceaneng.2015.01.014.
Najafzadeh, M. and Azamathulla, H.M. (2013), "Neuro-fuzzy GMDH to predict the scour pile groups due to waves", *J. Comput. Civil Eng.*, **29**, 4014068. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000376.
Najafzadeh, M. and Bonakdari, H. (2016), "Application of a neuro-fuzzy GMDH model for predicting the velocity at limit of deposition in storm sewers", *J. Pipeline Syst. Eng. Pract.*, 8:6016003. https://doi.org/10.1061/(ASCE)PS.1949-1204.0000249.
Najafzadeh, M. Barani, G.A. and Azamathulla, H.M. (2013), "GMDH to predict scour depth around a pier in cohesive soils", *Appl. Ocean Res.*, **40**, 35-41. https://doi.org/10.1016/j.apor.2012.12.004.
Prakash, S. and Sharma, H.D. (1990), *Pile foundations in engineering practice*, John Wiley & Sons
Samui, P. (2008), "Prediction of friction capacity of driven piles in clay using the support vector machine", *Can. Geotech. J.*, **45**, 288-295. https://doi.org/10.1139/T07-072.
Samui, P. (2012), "Determination of ultimate capacity of driven piles in cohesionless soil: A multivariate adaptive regression spline approach", *Int. J. Numer. Analy. Meth. Geomech.*, **36**(11), 1434-1439. https://doi.org/10.1007/s00521-012-1043-x.
Samui, P. and Kim, D. (2013), "Least square support vector machine and multivariate adaptive regression

spline for modeling lateral load capacity of piles", *Neural Comput. Appl.*, **23**, 1123-1127. https://doi.org/10.1007/s00366-019-00808-y.

Sarir, P., Chen, J., Asteris, P.G., Armaghani, D.J. and Tahir, M.M. (2019), "Developing GEP tree-based, neuro-swarm, and whale optimization models for evaluation of bearing capacity of concrete-filled steel tube columns", *Eng. Comput.*, 1-19. https://doi.org/10.1007/s00366-019-00808-y.

Sette, S. and Boullart, L. (2001), "Genetic programming: principles and applications", *Eng. Appl. Artif. Intell.*, **14**, 727-736. https://doi.org/10.1016/S0952-1976(02)00013-1.

Shahin, M.A., Maier, H.R. and Jaksa, M.B. (2002), "Predicting settlement of shallow foundations using neural networks", *J. Geotech. Geoenviron. Eng.*, **128**, 785-793. https://doi.org/10.1061/(ASCE)1090-0241(2002)128:9(785).

Sinha, S.K. and Wang, M.C. (2008), "Artificial neural network prediction models for soil compaction and permeability", *Geotech. Geol. Eng.*, **26**, 47-64. https://doi.org/10.1007/s10706-007-9146-3.

Toghroli, A., Mohammadhassani, M., Suhatril, M., Shariati, M. and Ibrahim, Z. (2014), "Prediction of shear capacity of channel shear connectors using the ANFIS model", *Steel Compos. Struct.*, **17**, 623-639. http://dx.doi.org/10.12989/scs.2014.17.5.623.

Tomlinson, M. and Woodward, J. (2007), *Pile design and construction practice*. Crc Press

Wang, M. Shi, X., Zhou, J. and Qiu, X. (2018), "Multi-planar detection optimization algorithm for the interval charging structure of large-diameter longhole blasting design based on rock fragmentation aspects", *Eng. Optim.*, **50**, 2177-2191. https://doi.org/10.1080/0305215X.2018.1439943.

Wu, Y., Zhang, K., Fu, L., Liu, J. and He, J. (2019), "Performance of cement–soil pile composite foundation with lateral constraint", *Arab. J. Sci. Eng.*, **44**, 4693-4702. https://doi.org/10.1007/s13369-018-3519-1.

Xu, C., Gordan, B., Koopialipoor, M., Armaghani, D.J., Tahir, M.M. and Zhang, X. (2019a), "Improving performance of retaining walls under dynamic conditions developing an optimized ANN based on ant colony optimization technique", *IEEE Access.* **7**, 94692-94700. https://doi.org/10.1109/ACCESS.2019.2927632.

Xu, H., Zhou, J., G Asteris, P., Jahed Armaghani, D. and Tahir, M.M. (2019b), "Supervised machine learning techniques to the prediction of tunnel boring machine penetration rate", *Appl. Sci.*, **9**, 3715. https://doi.org/10.3390/app9183715.

Yang H, Liu J, Liu B (2018) Investigation on the cracking character of jointed rock mass beneath TBM disc cutter. Rock Mech Rock Eng 51:1263–1277. https://doi.org/10.1007/s00603-017-1395-8.

Yang H, Wang H, Zhou X (2016) Analysis on the damage behavior of mixed ground during TBM cutting process. Tunn Undergr Sp Technol 57:55–65. https://doi.org/10.1016/j.tust.2016.02.014.

Yang, H.Q., Zeng, Y.Y., Lan, Y.F. and Zhou, X.P. (2014), "Analysis of the excavation damaged zone around a tunnel accounting for geostress and unloading", *Int. J. Rock Mech. Min. Sci.*, **69**, 59-66. https://doi.org/10.1016/j.ijrmms.2014.03.003.

Young-Su K. and Byung-Tak, K. (2006), "Use of artificial neural networks in the prediction of liquefaction resistance of sands", *J. Geotech. Geoenviron. Eng.*, **132**, 1502-1504. https://doi.org/10.1061/(ASCE)1090-0241(2006)132:11(1502).

Zhang, W., Wu, C., Li, Y., Wang, L. and Samui, P. (2019), "Assessment of pile drivability using random forest regression and multivariate adaptive regression splines", *Georisk Assess. Manag. Risk Eng. Syst. Geohazards.* 1-14. https://doi.org/10.1080/17499518.2019.1674340.

Zhou, J., Asteris, P.G., Armaghani, D.J. and Pham, B.T. (2020a), "Prediction of ground vibration induced by blasting operations through the use of the Bayesian Network and random forest models", *Soil Dyn. Earthq. Eng.*, **139**, 106390. https://doi.org/10.1016/j.soildyn.2020.106390.

Zhou, J., Li, C., Koopialipoor, M., Jahed Armaghani, D. and Thai Pham, B. (2020b), "Development of a new methodology for estimating the amount of PPV in surface mines based on prediction and probabilistic models (GEP-MC)", *Int. J. Min. Reclam. Environ.*, **35**(1), 48-68.https://doi.org/10.1080/17480930.2020.1734151.

Zhou, J., Li, E., Yang, S., Wang, M., Shi, X., Yao, S. and Mitri, H.S. (2019), "Slope stability prediction for circular mode failure using gradient boosting machine approach based on an updated database of case histories", *Saf. Sci.*, **118**, 505-518. https://doi.org/10.1016/j.ssci.2019.05.046.

Zhou, J., Qiu, Y., Armaghani, D.J., Zhang, W., Li, C., Zhu, S. and Tarinejad, R. (2020c), “Predicting TBM penetration rate in hard rock condition: A comparative study among six XGB-based metaheuristic techniques”, *Geosci. Front*., https://doi.org/10.1016/j.gsf.2020.09.020

Zhou, J., Shi, X., Du, K., Qiu, X., Li, X. and Mitri, H.S. (2016), “Feasibility of random-forest approach for prediction of ground settlements induced by the construction of a shield-driven tunnel”, *Int. J. Geomech*., **17**(6), 4016129. https://doi.org/10.1061/(ASCE)GM.1943-5622.0000817.

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