DOI: http://dx.doi.org/10.12989/gae.2010.2.4.253

High-precision modeling of uplift capacity of suction caissons using a hybrid computational method

Amir Hossein Alavi*[1], Amir Hossein Gandomi[1,2a], Mehdi Mousavi[3] and Ali Mollahasani[4]

[1]*School of Civil Engineering, Iran University of Science and Technology, Tehran, Iran*
[2]*College of Civil Engineering, Tafresh University, Tafresh, Iran*
[3]*Department of Civil Engineering, Faculty of Engineering, Arak University, Arak, Iran*
[4]*Department of Civil Engineering, Ferdowsi University of Mashhad, Mashhad, Iran*

(Received July 22, 2010, Accepted October 1, 2010)

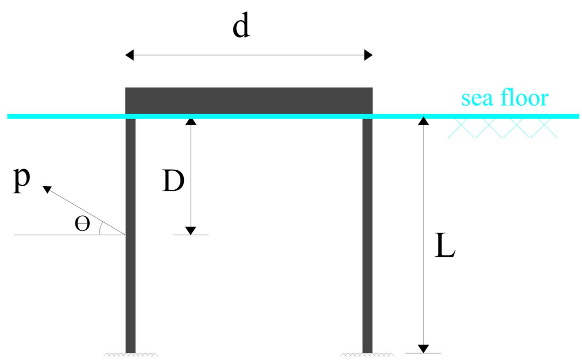
Abstract. A new prediction model is derived for the uplift capacity of suction caissons using a hybrid method coupling genetic programming (GP) and simulated annealing (SA), called GP/SA. The predictor variables included in the analysis are the aspect ratio of caisson, shear strength of clayey soil, load point of application, load inclination angle, soil permeability, and loading rate. The proposed model is developed based on well established and widely dispersed experimental results gathered from the literature. To verify the applicability of the proposed model, it is employed to estimate the uplift capacity of parts of the test results that are not included in the modeling process. Traditional GP and multiple regression analyses are performed to benchmark the derived model. The external validation of the GP/SA and GP models was further verified using several statistical criteria recommended by researchers. Contributions of the parameters affecting the uplift capacity are evaluated through a sensitivity analysis. A subsequent parametric analysis is carried out and the obtained trends are confirmed with some previous studies. Based on the results, the GP/SA-based solution is effectively capable of estimating the horizontal, vertical and inclined uplift capacity of suction caissons. Furthermore, the GP/SA model provides a better prediction performance than the GP, regression and different models found in the literature. The proposed simplified formulation can reliably be employed for the pre-design of suction caissons. It may be also used as a quick check on solutions developed by more time consuming and in-depth deterministic analyses.

Keywords: suction caissons; uplift capacity; genetic programming; simulated annealing; nonlinear modeling.

1. Introduction

A suction caisson is a steel tube closed at the top and open at the bottom. It serves as an anchor by penetrating the seafloor bottom sediments. Suction caissons are the most widely-used anchorage systems in offshore structures. This is because of their relatively easier installation process and lower cost compared with the conventional driven pile foundations (Colliat *et al.* 2002). In addition, suction caissons provide greater resistance to lateral loads than other alternatives. A typical sketch

*Corresponding author, E-mail: ah_alavi@hotmail.com
[a]E-mail: a.h.gandomi@gmail.com



L: Length of caisson
d: Diameter of caisson in plan
D: Depth of load application point from soil surface
P: Load applied to caisson
θ: Load inclination angle

Fig. 1 A typical sketch of suction caisson

of a suction caisson is shown in Fig. 1. The first step of penetration of suction caisson into the seabed is due to its self weight. The rest penetration is made by means of suction created by pumping water out of the caisson.

These systems, also called “buckets”, “skirted foundation” and “suction anchors”, were first introduced by Senpere and Auvergne (1982) as mooring anchors for a storage tanker in an offshore project in Denmark. Some of the suction caissons design considerations are listed below:

- Submerged weight of caisson and ballast if applied
- Suction pressure created across the caisson under tensile loading
- Weight of the soil plug inside the caisson
- Skin friction
- Soil shear strength at the caisson base

Some of the following advantages make the use of suction caissons reasonable:

i. Suction caissons are simple steel fabrications that can be designed to be lighter than the steel required for an equivalent pile foundation.
ii. The installation method is potentially much quicker and simpler than that for the other solutions. A foundation incorporation suction caisson can be deployed and installed within a matter of hours as a single simple operation. The installation is not significantly weather dependent.
iii. The installation method requires only a simple marine spread including a crane of sufficient capacity to lift units into place. Additional costs of ancillary equipment, such as pile driving hammer spreads, grouting spreads and consumables required by the other installation methods, can remarkably be saved.

Uplift capacity is a critical issue in the performance analysis of suction caissons. The increased use of suction caissons implies the need to develop comprehensive mathematical models to assess their uplift capacity. Genetic algorithm (GA) is a powerful stochastic search and optimization method based on the principles of genetics and natural selection. GA has been shown to be suitably robust for a wide variety of complex geotechnical problems (*e.g.* Simpson and Priest 1993, McCombie and Wilkinson 2002, Levasseur *et al.* 2009). Genetic programming (GP) (Koza 1992, Banzhaf *et al.* 1998) is an alternative approach for behavior modeling of geotechnical engineering tasks. GP is a developing subarea of evolutionary algorithms inspired from the Darwin's evolution theory. It may generally be defined as a specialization of GA where the solutions are computer programs rather than fixed-length binary strings. The main advantage of GP over the conventional statistical methods and other soft computing tools is its ability to generate prediction equations without assuming prior form of the existing relationship. The developed equations can easily be manipulated in practical circumstances. In contrast with artificial neural networks (ANNs) and GAs, application of GP in the field of civil engineering is quite new and original. Classical GP and its variants have recently been used to derive greatly simplified formulas for civil engineering problems (*e.g.* Johari *et al.* 2006, Javadi *et al.* 2006, Baykasoglu *et al.* 2008, Cabalar and Cevik 2009, Alavi and Gandomi 2010, Gandomi *et al.* 2010). Recent studies have also shown that the GP-based techniques possess some obvious superiority than ANNs in dealing with geotechnical problems (*e.g.*, Rezania and Javadi 2007, Kayadelen *et al.* 2009).

Simulated annealing (SA) is a general stochastic search algorithm used for solving optimization problems. The Metropolis algorithm, the foundation of SA, was proposed by Metropolis *et al.* (1953) to simulate the annealing process. This algorithm was first applied to optimization problems by Kirkpatrick *et al.* (1983) and Cerny (1985). SA is very useful for solving several types of optimization problems with nonlinear functions and multiple local optima. Folino *et al.* (2000) and Deschaine *et al.* (2000) combined GP and SA to make a hybrid algorithm with better efficiency. The SA strategy was used to decide the acceptance of a new individual. It was shown that introducing this strategy into the GP process improves the profitably of GP. Applications of the hybrid GP/SA technique to solve problems in civil engineering are conspicuous by their near absence. Recently, Alavi *et al.* (2010a) utilized this hybrid method to formulate the flow number of asphalt mixes.

The GP/SA approach is useful in characterizing the complex behavior of suction caissons by directly extracting the knowledge contained in the experimental data. The main purpose of this paper is to utilize GP/SA to obtain a generalized relationship between the uplift capacity of suction caissons and several influencing parameters. A reliable database of previously published experimental results is used for developing the model. The performance of the GP/SA model is further compared with that of the tree-based GP, regression and several models found in the literature.

2. Review of previous studies

Several investigations on the complex behavior of suction caissons are reported in the literature. On the basis of these researches, different empirical and theoretical models are proposed. A large number of field tests on small-scale and full-scale caissons are performed to determine the caissons installation characteristics and their axial and lateral load capacities (*e.g.* Hogervorst 1980, Tjelta 1995). Geotechnical centrifuge tests are carried out on model suction caissons for simulating the stress conditions and soil response at field scale (Clukey *et al.* 1995, Randolph *et al.* 1998). Laboratory tests are conducted by some researchers on model suction caissons under 1 g and controlled laboratory conditions (*e.g.* El-gharbawy *et al.* 1999, Rao *et al.* 1997, Byrne and Houlsby 2002). Despite providing valuable geotechnical information, the field tests and laboratory testing of model caissons are quite costly, time-consuming and subjected to various limitations.

Detailed studies are done to investigate the suction caisson behavior involving extensive axisymmetric and three-dimensional numerical simulations (*e.g.*, Erbrich and Tjelta 1999, Sukumaran and McCarron 1999, Deng and Carter 1999a, b, 2002, Maniar 2000). Finite element method (FEM) analysis was the approach considered to estimate the capacity of suction caisson under different loading and drainage conditions. Recently, plastic limit analysis (PLA) has been applied to the analysis of suction caissons subjected to a variety of loading conditions. Aubeny *et al.* (2001, 2003, 2005) and Aubeny and Murff (2005) applied PLA to obtain simplified limit solutions for the capacity of suction caissons. The ultimate load capacity calculated from PLA provides useful benchmarks for evaluating the accuracy of the FEM solutions.

There are some other researches that deal with the estimation of the uplift capacity of suction caissons using artificial neural network (ANN). Rahman *et al.* (2001) employed a three-layered back-propagation ANN with Levenberg-Marquardt optimization for the prediction of uplift capacity. Pai (2005) proposed a hybrid neuro-genetic network (NGN) model for the uplift capacity prediction. In the NGN model, the multilayer feed forward neural network was used as its host architecture and genetic algorithms was employed to determine its weights. Recently, Rezania *et al.* (2008) presented a new evolutionary polynomial regression (EPR) method for the analysis of the uplift capacity of suction caissons. A transparent and structured representation of the system was generated using EPR.

3. Genetic programming

GP is a symbolic optimization technique that creates computer programs to solve a problem using the principle of Darwinian natural selection (Koza 1992). The breakthrough in GP then came in the late 1980s with the experiments on symbolic regression. GP was introduced by Koza (1992) as an extension of GA. Most of the genetic operators used in GA can also be implemented in GP with minor changes. The main difference between GP and GA is the representation of the solution. GA creates a string of numbers that represent the solution. The GP solutions are computer programs represented as tree structures and expressed in a functional programming language (like LISP) (Koza 1992). In other words, in GP, the evolving programs (individuals) are parse trees that can vary in length throughout the run rather than fixed-length binary strings. Essentially, this is the beginning of computer programs that program themselves (Koza 1992). Since GP often evolves computer programs, the solutions can be executed without post-processing, while coded binary strings typically evolved by GA require post-processing. The traditional optimization techniques, like GA, are generally used in parameter optimization to evolve the best values for a given set of model parameters. GP, on the other hand, gives the basic structure of the approximation model together with the values of its parameters (Javadi and Rezania 2009). GP optimizes a population of computer programs according to a fitness landscape determined by a program ability to perform a given computational task. The fitness of each program in the population is evaluated using a fitness function. Thus, the fitness function is the objective function GP aims to optimize (Torres *et al.* 2009).

This classical GP approach is referred to as tree-based GP. A population member in tree-based GP is a hierarchically structured tree comprising functions and terminals. The functions and terminals are selected from a set of functions and a set of terminals. For example, the function set F can

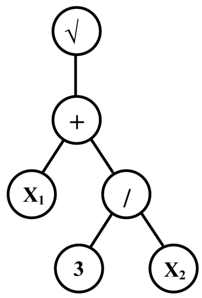


Fig. 2 Tree representation of a GP model ($\sqrt{(X_1+3/X_2)}$)

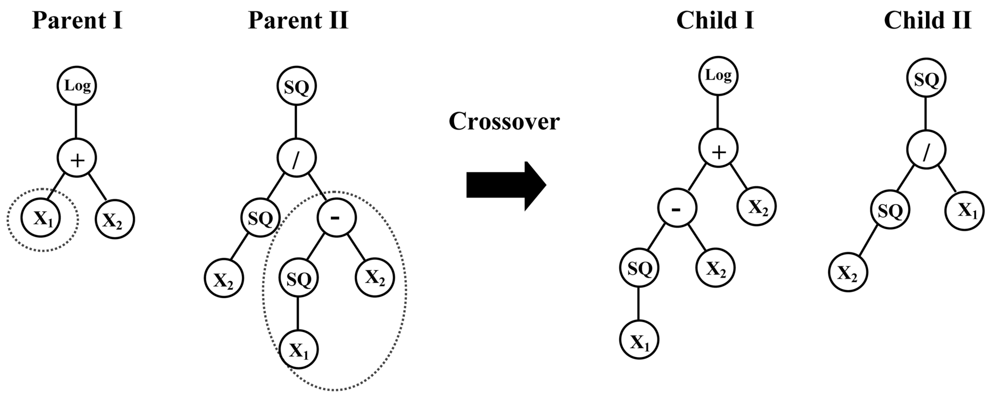


Fig. 3 Typical crossover operation in GP

contain the basic arithmetic operations (+, –, ×, /, etc.), Boolean logic functions (AND, OR, NOT, etc.), or any other mathematical functions. The terminal set T contains the arguments for the functions and can consist of numerical constants, logical constants, variables, etc. The functions and terminals are chosen at random and constructed together to form a computer model in a tree-like structure. An example of a tree representation of a GP model is illustrated in Fig. 2.

Creation of the initial population is a blind random search for solutions in a large space of possible solutions. Once a population of models is created at random, the GP algorithm evaluates the individuals, selects individuals for reproduction, and generates new individuals by mutation, crossover and direct reproduction (Koza 1992). During the crossover procedure, a point on a branch

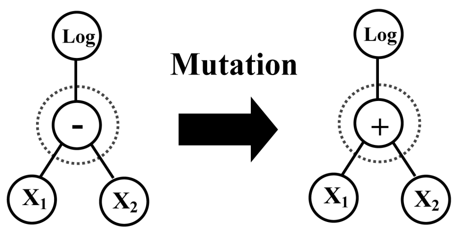


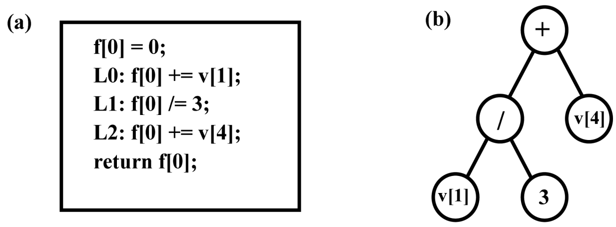
Fig. 4 Typical mutation operation in GP

of each solution (program) is selected at random and the set of terminals and/or functions from each program are then swapped to create two new programs (see Fig. 3). The evolutionary process continues by evaluating the fitness of the new population and starting a new round of reproduction and crossover. During this process, the GP algorithm occasionally selects a function or terminal from a model at random and mutates it (see Fig. 4). The best program that appeared in any generation, the best-so-far solution, defines the output of the GP algorithm (Koza 1992). In the following subsections, the coupled algorithm of GP and SA, GP/SA, is briefly described.

3.1 Hybrid genetic programming-simulated annealing algorithm

In this paper, GP with a SA-based selection strategy is employed for developing the prediction models. In this coupled algorithm, the SA strategy is used to select new individuals (Folino *et al.* 2000, Deschaine *et al.* 2000, Francone 2004). The GP system used in this study is linear genetic programming (LGP) (Brameier and Banzhaf 2001, 2007). LGP is a new subset of GP with a linear structure similar to the DNA molecule in biological genomes. The main characteristic of LGP in comparison with the traditional tree-based GP is that expressions of a functional programming language (like LISP) are substituted by programs of an imperative language (like C/C++) (Brameier and Banzhaf 2001). Fig. 5 presents a comparison of the program structures in LGP and tree-based GP. As shown in Fig. 5(a), a linear genetic program can be seen as a data flow graph generated by multiple usage of register content. That is, on the functional level the evolved imperative structure denotes a special directed graph. As can be observed from Fig. 5(b), in tree-based GP, the data flow is more rigidly determined by the tree structure of the program (Brameier and Banzhaf 2001). In the LGP system utilized here, an individual program is interpreted as a variable-length sequence of simple C instructions.

LGP allows structurally non-effective codes to coexist with effective codes in programs (Brameier and Banzhaf 2001). An instruction of a linear genetic program is called "effective" at its position if it affects the program output. The non-effective codes in genetic programs represent instructions without any influence on the program behavior. These codes act as a protection reducing the effect of variation on the effective code. Because of the program structure in LGP, the non-effective codes can be detected and eliminated much easier than in tree-based GP and other comparable interpreting systems (Francone and Deschaine 2004). Thus, the linear genetic code is interpreted more efficiently. Another feature of the LGP system is that the non-effective codes can be removed before a linear genetic program is executed during fitness calculation. This is done by copying all effective instructions to a temporary program buffer and results in an enormous acceleration in the LGP



y = f[0] = (v[1] / 3) + v[4]

Fig. 5 Comparison of the GP program structures: (a) LGP, (b) Tree-based GP (after Alavi *et al.* 2010b) execution speed. Moreover, almost all computer architectures represent computer programs in a linear fashion. In other words, computers do not naturally run tree-shaped programs. Hence, slow interpreters have to be used as part of tree-based GP. Conversely, by evolving the binary bit patterns in LGP, the use of an expensive interpreter (or compiler) is avoided. Consequently, LGP can run several orders of magnitude faster than comparable interpreting systems (Poli *et al.* 2007). The enhanced speed of LGP, and therefore GP/SA, permits conducting many runs in realistic timeframes. This leads to deriving consistent, high-precision models with little customization (Francone and Deschaine 2004, Deschaine *et al.* 2000).

3.1.1 The SA algorithm

SA makes use of the Metropolis algorithm (Metropolis *et al.* 1953) for the computer simulation of annealing. Annealing is a process in which a metal is heated to a high temperature and then is gradually cooled to relieve thermal stresses. During the cooling process, each atom takes a specific position in the crystalline structure of the metal. By changing the temperature, this crystalline structure changes to a different configuration. An internal energy, E, can be measured and assigned to each state of crystalline structure of the metal which is achieved during the annealing process. At each step of the cooling process, if the temperature does not decrease quickly the atoms are allowed to adjust to a stable equilibrium state of least energy. It is evident that changing of the crystalline structure of a metal, through the annealing, is associated with a changing of the internal energy as ΔE. However, as the metal temperature drops down gradually, the overall trend of changing internal energy follows a decreasing process but sometimes the energy may increase by chance. The probability of acceptance of an increase in internal energy by ΔE is given by Boltzmann's probability distribution function as follows

$$P(\Delta E) = e^{\frac{-\Delta E}{KT}} \tag{1}$$

where T is the temperature of the metal in Kelvin's temperature scale and K is the Boltzmann's constant. The crystalline structure of a metal achieves near global minimum energy states during the process of annealing. This process is simulated by SA to find the minimum of a function in a certain design space. The objective function corresponds to the energy state and moving to any new set of design variables corresponds to a change of the crystalline structural state.

3.1.2 The GP/SA algorithm

Considering the above explanations for GP and SA, the coupled GP/SA algorithm uses the following main steps to evolve a computer program (Deschaine *et al.* 2000, Francone 2004):

I. A single program is initially created at random. This is the "parent" program for the first repetition of the learning cycle.
II. The parent program is copied.
III. A search operator, crossover or mutation, transforms the copy of the parent program. The transformed copy is called "child" program or "offspring" program. The crossover operator produces two children programs. But only one of these programs is compared with the parent as a candidate to replace the parent program.
IV. The fitness value of the both parent and child program is calculated.
V. Based on the fitness value of the child and parent program, the SA algorithm decides whether to replace the parent program with the child program. If the child has better fitness than the

parent, the child always replaces its parent. If the child has worse fitness than the parent, the child replaces the parent probabilistically. The probability of replacement depends on how much worse the fitness of the child is than the parent and also on the SA temperature, T. As the annealing process continues, T is gradually reduced at each nth iteration. This means that, for the program, the probability of replacing a worse child to a better parent gets lower and lower as the run continues. If the child program replaces the parent program then the child program becomes the new parent for the next cycle. Alternatively, if the parent program is not replaced by the child, it remains as the parent program for the next cycle.

VI. If the termination or convergence conditions are satisfied the process is terminated. Otherwise, the process is continued going step III.

A comprehensive description of the GP/SA algorithm involved parameters can be found in (Francone 2004).

4. Modeling of uplift capacity of suction caissons

The suction caisson capacity is provided due to the active and passive pressure mobilized as a result of the horizontal translation of the caisson. In deeper suctions, the lateral resistance is afforded by soil flow around the caisson. Therefore, the obtained holding capacity depends on the suction pressure applied, soil conditions at site, load attachment point, and anchor geometry. This paper considers the feasibility of using the GP/SA approach to obtain a prediction equation for the uplift capacity. The most important factors representing the uplift capacity behavior were selected based on the literature review (Deng and Carter 1999a, b, 2002, Rahman *et al.* 2001, Pai 2005, Rezania *et al.* 2008) and after a trial study. Consequently, the uplift capacity formulation was considered to be as follows

$$Q = f\left(\frac{L}{d}, \frac{D}{L}, \sin(\theta), S_u, Ln(T_k)\right) \tag{2}$$

where,

Q (kPa) : Uplift capacity of suction caisson

L/d : Embedded length of caisson to its diameter

D/L : Relative depth of lug to which caisson force is applied, where D is the distance from the lateral force point of application to the soil surface

θ (Rad) : Angle that chain force makes with the horizontal given by

$$\theta = \tan^{-1}\left(\frac{\text{Vertical components of the ultimate inclined load}}{\text{Horizontal components of the ultimate inclined load}}\right) \tag{3}$$

S_u (kPa): Undrained soil shear strength at depth of caisson tip

$T_k = k/v$: Non-dimensional loading rate parameter, where k is the soil permeability and v is the loading rate (steady velocity) at which caisson is pulled from the ground

L/d, D/L and θ represent the caisson geometry and load attachment point. S_u and T_k denote the soil conditions at the site. The significant influence of these parameters in determining Q is well understood. As the embedment length of the caisson (L/d) increases, the skin friction component proportionately increases due to the inclination in the caisson and passive earth pressure. The resistance changes from the passive earth pressure to skin friction by changing the inclination (θ) from 0^{o} to 90^{o}. For the inclined loading conditions, both components contribute to the uplift capacity (Rao *et al.* 2006). The effect of the load application point (D/L) on the uplift capacity has rarely been investigated by researchers. Deng and Carter (2000) showed that the maximum inclined uplift capacity of suction caissons is usually obtained when the load is applied at a depth of approximately 0.63 times the length of the caisson. In clayey types of soil, increases in S_u cause an improvement in the skin friction (due to increase in cohesion) and passive resistance. Deng and Carter (1999a) defined a term, called bottom breakout resistance factor, for the evaluation of the uplift capacity of suction caisson under partially drained conditions. This term incorporates the effect of T_k as an indicator of the resistance developed at the bottom of the caisson.

The best model was chosen on the basis of a multi-objective strategy as follows:

i. The simplicity of the model, although this was not a predominant factor.
ii. Providing the best fitness value on the learning set of data.
iii. Providing the best fitness value on a validation set of data.

The first objective can be controled by the user through the parameter settings (*e.g.*, program size). The other objectives were controlled via coefficient of determination (R^2), mean squared error (MSE) and mean absolute error (MAE). R^2, MSE and MAE are given in the form of formulas as follows

$$R^2 = \frac{\left(\Sigma_{i=1}^{n}(h_i - \overline{h_i})(t_i - \overline{t_i})\right)^2}{\Sigma_{i=1}^{n}(h_i - \overline{h_i})^2 \Sigma_{i=1}^{n}(t_i - \overline{t_i})^2} \tag{4}$$

$$MSE = \frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n} \tag{5}$$

$$MAE = \frac{\sum_{i=1}^{n}|h_i - t_i|}{n} \tag{6}$$

4.1 Experimental database and data preprocessing

The database contains 62 experimental test results from 12 independent studies. It includes laboratory model-scale, centrifugal and field test results gathered by Rahman *et al.* (2001). The data used in this study are for the clayey soils covering a range of loading rates. The slow and high rates respectively correspond to fully drained conditions and undrained loading cases. The intermediate loading rates correspond to partial drainage conditions. The database consists of the measurements of several variables such as L/d, D/L, θ (Rad), S_u (kPa), T_k, and Q (kPa). To visualize the distribution of the samples, the data are presented by histogram plots (Fig. 6). The complete list of the data is presented in Table A.1 of Appendix A.

Overfitting is one of the principal problems in machine learning generalization. It is a case in which the error on the learning set is driven to a very small value, but when new data is presented to the model, the error is large. An efficient approach to prevent overfitting is to test other

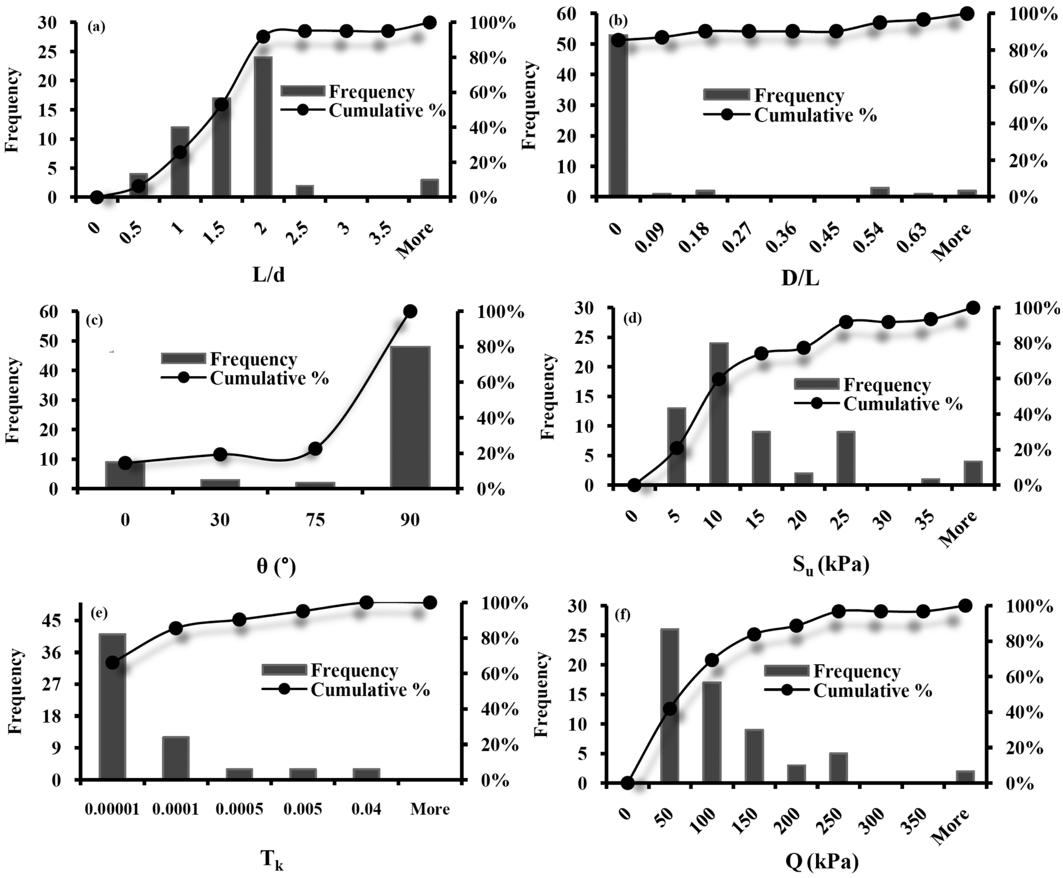


Fig. 6 Histograms of the variables used in the model development

individuals from the run on a validation set to find a better generalization (Banzhaf *et al.* 1998). This technique was used in this study for improving the generalization of the models. For this purpose, the available data sets were randomly divided into learning, validation and testing subsets. The learning data were used for training (genetic evolution). The validation data were used to specify the generalization capability of the evolved programs on the data that were not included in the learning process (model selection). In other words, the learning and validation data sets were used to select the best evolved programs and included in the training process. Thus, they were categorized into one group referred to as training data. The testing data were finally used to measure the performance of the models obtained by GP/SA on data that played no role in building the models. This technique provides decent results as long as the models perform well on the learning data sets (Banzhaf *et al.* 1998). In order to obtain a consistent data division, several combinations of the training and testing sets were considered. Of the 62 data, 41 data vectors were used for the learning process and 10 data were taken as the validation data. The remaining 11 sets were used for the testing of the derived models.

Some of the employed variables may be fundamentally interdependent. The first step in the analysis of interdependency of the data is to make a careful study of what it is that these variables are measuring, noting any highly correlated pairs. High positive or negative correlation coefficients

Table 1 Correlation coefficients between all pairs of the explanatory variables

Variable	L/d	S_u	$Ln(Tk)$	$\sin(\theta)$	D/L
L/d	1.000	–0.091	–0.325	0.225	0.366
S_u	–0.091	1.000	–0.438	–0.668	0.099
$Ln(Tk)$	–0.325	–0.438	1.000	0.289	–0.204
$\sin(\theta)$	0.225	–0.668	0.289	1.000	–0.417
D/L	0.366	0.099	–0.204	–0.417	1.000

Table 2 Descriptive statistics of the variables used in the model development

Parameters	Range	Standard deviation	Skewness	Kurtosis	Mean	Normalized form
Inputs						
L/d	0.23–4	0.77	1.09	2.86	1.59	$(L/d)/5$
D/L	0–0.69	0.17	2.89	7.07	0.06	D/L
θ (Rad)	0–$\pi/2$	0.60	−1.58	0.58	0.4π	$\sin(\theta)$
S_u (kPa)	1.8–38	10.0	1.35	1.03	11.75	$S_u/50$
T_k	E-5–0.04	0.01	4.25	16.8	22E-4	$Ln(T_k)/-15$
Output						
Q (kPa)	10.1–387.2	81.67	1.74	3.51	90.06	Q / 400

between the pairs may lead to poor performance of the models. This interdependency can cause problems in analysis as it will tend to exaggerate the strength of relationships between the variables. This is a simple case commonly known as the problem of multi-collinearity (Dunlop and Smith 2003). Thus, the correlation coefficients between all possible pairs were determined. The correlation coefficients between the pairs are shown in Table 1. As can be seen in this table, there are not high correlations between the predictor variables.

Although normalization is not strictly necessary in the GP-based analyses, better results are usually reached after normalizing the variables. This is mainly due to influence of unification of the variables, no matter their range of variation. Thus, both input and output variables were normalized between 0 and 1. Selection of the optimal method for normalizing the data was based on controlling several normalization methods (Swingler 1996). The ranges, normalized values and statistics of different input and output parameters involved in the model development are given in Table 2.

4.2 GP/SA-based formulation for uplift capacity of suction caissons

The available database was used for the development of the GP/SA prediction model. Various parameters are involved in the GP/SA predictive algorithm. The parameter selection will affect the model generalization capability of GP/SA. The parameter settings are shown in Table 3. Several runs were conducted to come up with a parameterization of GP/SA that provided enough robustness and generalization to solve the problem. The GP/SA parameters were changed for different runs. The proper number of temperature levels depends on the number of possible solutions. It sets the number of temperature levels that the GP/SA algorithm uses until the run is terminated. Number of iterations per temperature level sets the number of times a new child program is created from the parent program at each temperature level. Three levels were set for the number of temperature levels parameter and two levels were used for the number of iterations. Temperature in the SA algorithm is just a number that controls the probability that a mutated child program will replace the parent program. Start and stop temperatures are respectively the values that a program uses for temperatures at the first and last temperature levels in a run. The initial and maximum program size parameters directly influence the size of the search space and the number of solutions explored within the search space. These parameters are measured in bytes. Two optimal values were set for the maximum program size as tradeoffs between the running time and the complexity of the evolved solutions. It is notable that the crossover rate parameter in the GP/SA algorithm sets the balance between the uses of the search operators (crossover and mutation). A value of 50% means that 50% of time the used search operator will be the crossover operator. The mutation operator will therefore be employed in the other 50% of time by the GP/SA algorithm (Francone 2004). Two levels were considered for the crossover rate. Basic arithmetic operators and mathematical functions were also utilized to get the optimum models. The values of the other involved parameters were selected based on some previously suggested values (Alavi *et al.* 2010a) and also after performing many preliminary runs and checking the performance. There are $3 \times 2 \times 2 \times 2 = 24$ different combinations of the parameters. All of these combinations were tested and 10 replications for each combination were performed. Therefore, the total number of runs was equal to $24 \times 10 = 240$. The GP/SA algorithm was implemented using Discipulus (Conrads *et al.* 2004) software. In order to find models with minimum error, each run was performed with large numbers of temperature levels and iterations. The program was run until there was no longer significant improvement in the performance of the models or the runs terminated automatically. Each run was observed while in progress for overfitting. For this aim, situations were checked in which the fitness of the samples for the learning of GP/SA was negatively correlated with the fitness on the validation data sets. To

Table 3 Parameter settings for the GP/SA algorithm

Parameter	Settings
Number of temperature levels	1000, 3000, 10000
Number of iterations per temperature level	1000, 2000
Start temperature	5
Stop temperature	0.01
Fitness function error type	Squared error
Crossover rate (%)	50, 95
Homologous crossover (%)	95
Probability of randomly generated parent in crossover (%)	99
Block mutation rate (%)	30
Instruction mutation rate (%)	30
Data mutation rate (%)	40
Offspring choice rate (%)	50
Replacement scaling factor	1
Maximum program size	128, 256
Initial program size	80
Function set	$+, -, \times, /, \sqrt{\ }$, sin, cos

evaluate the fitness of the evolved programs, the average of the squared raw errors was used. For the runs showing signs of overfitting, the GP/SA parameters were progressively changed so as to reduce the computational power available to the GP/SA algorithm until the observed overfitting was minimized. The resulting run was then accepted as the production run. The programs with the best performance on both of the learning and validation data sets were finally selected as the outcomes of each run.

The GP/SA-based formulation of the uplift capacity of suction caissons, Q, is as given below

$$Q(kPa)=400x_1\left(2\left(\frac{x_4}{2}\left(x_3\left(\frac{x_5}{((-2x_1^2+1-x_4)/x_1-2)}+\frac{1}{2}\right)-x_4-x_5+\frac{2x_1+2x_1^2-1}{x_5(-2x_1^2+1)}\left(\frac{2x_1^2-1+x_4}{x_1}+2\right)\right)+\frac{x_2}{2}+x_5\right)x_4+2x_4\right) \quad (7)$$

where,

$x_1 = (L/d)/5$
$x_2 = D/L$
$x_3 = \sin(\theta)$
$x_4 = S_u/50$
$x_5 = Ln(T_k)/-15$

Comparisons of the measured versus predicted uplift capacity values are shown in Fig. 7. The number of temperature levels and iterations were respectively equal to 3000 and 1000 for the optimal run. This run took 5 min and 32 s on a Pentium 4 personal computer with 3.00 GHz of processor speed and 1 Gb of memory. The number of the computer programs evolved and evaluated by the GP/SA algorithm during the conducted run was equal to 6,015,479. The final GP/SA program obtained at the end of the learning process in C++ is also given in Appendix B. This program can be run in any C++ environment. The resulting code may be linked to the optimizer and compiled or it may be called from the optimization routines (Deschaine 2000).

4.3 Tree-based GP-based formulation for uplift capacity of suction caissons

A tree-based GP analysis was performed to compare the hybrid GP and SA technique (GP/SA)

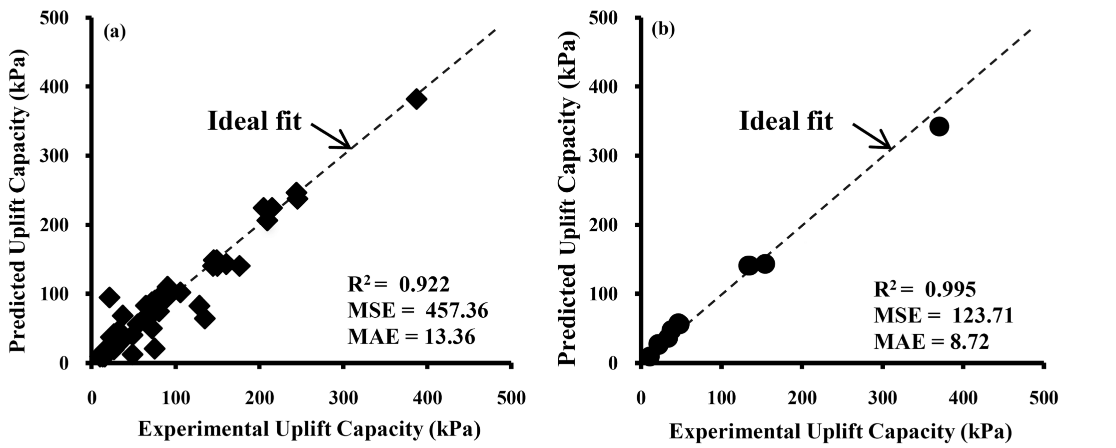


Fig. 7 Measured versus predicted uplift capacity using the GP/SA model: (a) training data, (b) testing data

Table 4 Parameter settings for the tree-based GP algorithm

Parameter	Settings
Function set	+, −, ×, /
Population size	100-1000
Maximum tree depth	10
Total generations	4000
Initial population	Ramped half-and-half
Sampling	Tournament
Expected no. of offspring method	Rank 89
Fitness function error type	linear error function
Termination	Generation 40
Minimum probability of crossover	0.1
Minimum probability of mutation	0.1
Real max level	30
Survival mechanism	Keep best

with a classical GP approach. After developing and controlling several models with different combinations of the input parameters, the best tree-based GP model was selected and presented as the optimal model. Various parameters involved in the traditional GP predictive algorithm are shown in Table 4. The parameters were selected based on some previously suggested values (Johari *et al.* 2006) and also after a trial and error approach. A large number of generations were tested to find a model with minimum error. A tree-based GP software, GPLAB (Silva 2007) in conjunction with subroutines coded in MATLAB, was used in this study.

The formulation of the uplift capacity of suction caissons, Q, for the best results by the tree-based GP algorithm, is as given below

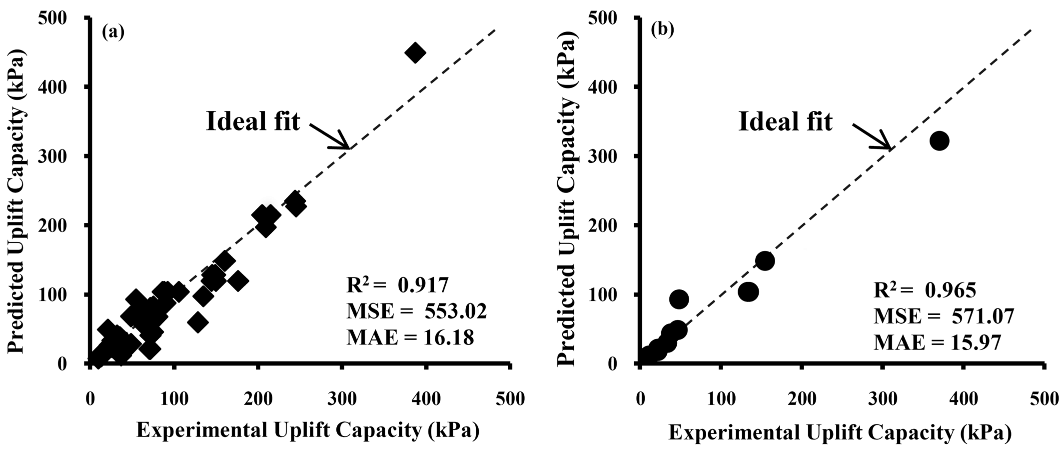


Fig. 8 Measured versus predicted uplift capacity using the tree-based GP model: (a) training data, (b) testing data

$$Q(kPa) = 400x_4(x_3+x_4)(((x_1+((x_2^3(x_1+3x_5)(x_4(x_5+2)+x_4))+x_2))+x_5)-x_4x_5) \tag{8}$$

in which x_1, ..., x_5 respectively represent L/d, D/L, θ, S_u, and T_k in their normalized forms shown in Table 2. Comparisons of the measured versus predicted uplift capacity using the tree-based GP model are shown in Fig. 8.

4.4 LSR-based formulation for uplift capacity of suction caissons

A multivariable least squares regression (LSR) (Ryan 1997) analysis was performed to have an idea about the predictive power of the GP/SA technique, in comparison with a classical statistical approach. The method of LSR is extensively used in regression analysis primarily because of its interesting nature. Under certain assumptions, LSR has some attractive statistical properties that have made it as a member of the most powerful and popular methods of regression analysis. LSR minimizes the sum-of-squared residuals for each equation, accounting for any cross-equation restrictions on the parameters of the system. If there are no such restrictions, this technique is identical to estimating each equation using single-equation ordinary least squares. Eviews software package (Maravall and Gomez 2004) was used to perform the regression analysis. The major task was to determine the LSR-based equation connecting the input variables to the output variable as

$$Q(kPa) = a_1\left(\frac{L}{d}\right) + a_2S_u + a_3Ln(T_k) + a_4\sin(\theta) + a_5\left(\frac{D}{L}\right) + a_6 \tag{9}$$

where a denotes coefficient vector. The LSR-based formulation of Q in terms of L/d, D/L, θ, S_u and T_k is as given below

$$Q(kPa) = -10.3601\left(\frac{L}{d}\right) + 8.32245S_u - 6.4006Ln(T_k) + 159.9838\sin(\theta) + 282.5551\left(\frac{D}{L}\right) - 202.3014 \tag{10}$$

Comparisons of the measured versus predicted uplift capacity using the LSR model are shown in Fig. 9.

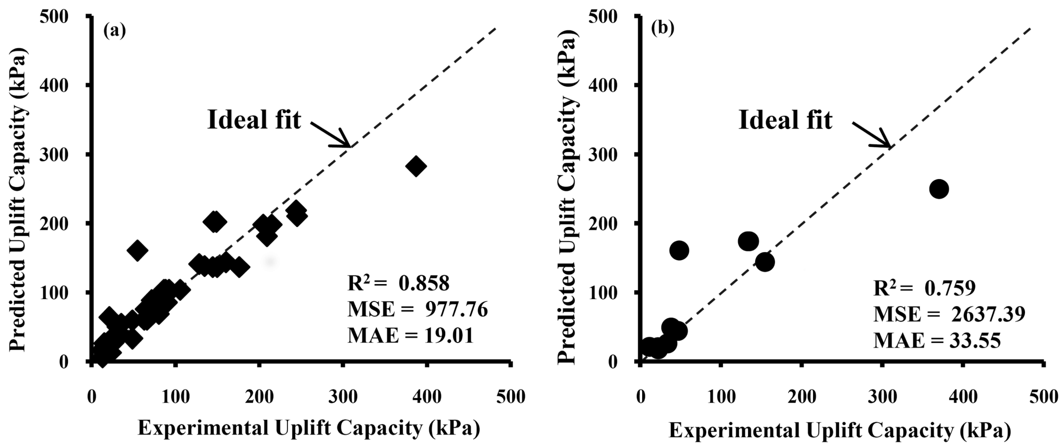


Fig. 9 Measured versus predicted uplift capacity using the LSR model: (a) training data, (b) testing data

5. Performance analysis and model validity

Based on a logical hypothesis (Smith 1986, Kasabov 1996), if a model gives a correlation coefficient (R) > 0.8, and the error (*e.g.*, MSE or MAE) values are at the minimum, there is a strong correlation between the predicted and measured values. The model can therefore be judged as very good. It can be observed from Fig. 7 that the GP/SA model with high R and low MSE and MAE values predicts the target values with a high degree of accuracy. The performance of the model on the testing data is better than that on the training (learning and validation) data. The GP/SA model has produced better results than the tree-based GP model. This indicates that applying the SA strategy to the GP process (GP/SA) has improved the efficiency of the traditional GP. The GP/SA model and also the tree-based GP solution significantly outperform the LSR-based model. It is notable that empirical modeling using the statistical regression techniques has significant limitations. Most commonly used regression analyses can have large uncertainties. It has major drawbacks pertaining to the idealization of complex processes, approximation, and averaging widely varying prototype conditions. In most cases, the best models developed using the commonly used statistical approaches are obtained after controlling a few equations established in advance. Thus, such models cannot efficiently consider the interactions between the dependent and independent variables. On the other hand, GP/SA introduces completely new characteristics and traits. One of the major advantages of the GP/SA approach over the traditional regression analyses is its ability to derive explicit relationships without assuming prior forms of the existing relationships. The best solutions (equations) evolved by this technique are determined after controlling numerous preliminary models, even millions of linear and nonlinear models. For instance, the proposed model for the estimation of the uplift capacity was selected among over 1,102,983,797 programs evolved and evaluated by the GP/SA method during the conducted 240 runs.

It is known that the models derived using the ANN, GP/SA, or other GP-based approaches, in most cases, have a predictive capability within the data range used for their calibration. Thus, the amount of data used in the training process of these techniques is an important issue, as it bears heavily on the reliability of the final models. To cope with this limitation, Frank and Todeschini (1994) argue that the minimum ratio of the number of objects over the number of selected variables for model acceptability is 3. It is also suggested that considering a higher ratio equal to 5 is safer. In the present study, this ratio is much higher and is equal to 62/5 = 12.4. Furthermore, new criteria recommended by Golbraikh and Tropsha (2002) were checked for the external validation of the GP/SA and tree-based GP models on the testing data sets. It is suggested that at least one slope of regression lines (k or k') through the origin should be close to 1. Also, the performance indexes of m and n should be lower than 0.1. Recently, Roy and Roy (2008) introduced a confirm indicator of the external predictability of models (R_m). For $R_m > 0.5$, the condition is satisfied. Either the squared correlation coefficient (through the origin) between predicted and experimental values (Ro^2), or the coefficient between experimental and predicted values (Ro'^2) should be close to R^2, and to 1. The validation criteria and the relevant results obtained by the models are presented in Table 5. As it is seen, the models satisfy the required conditions. The above facts ensure that the derived models, in particular the GP/SA formulation, are strongly valid, have the prediction power and are not chance correlations.

Performance statistics of the uplift capacity prediction models obtained by means of GP/SA, traditional GP, LSR, ANN (Rahman *et al.* 2001), NGN (Pai 2005), EPR (Rezania *et al.* 2008) and FEM (Deng and Carter 1999a, b, 2002) for the testing data sets are presented in Table 6. A

Table 5 Statistical parameters of the models for external validation

Item	Formula	Condition	GP/SA	Traditional GP
1	$R = \frac{\sum_{i=1}^{n}(h_i-\overline{h_i})(t_i-\overline{t_i})}{\sqrt{\sum_{i=1}^{n}(h_i-\overline{h_i})^2\sum_{i=1}^{n}(t_i-\overline{t_i})^2}}$	$0.8 < R$	0.998	0.982
2	$k = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{h_i^2}$	$0.85 < K < 1.15$	1.040	1.114
3	$k' = \frac{\sum_{i=1}^{n}(h_i \times t_i)}{t_i^2}$	$0.85 < K' < 1.15$	0.957	0.880
4	$m = \frac{R^2 - Ro^2}{R^2}$	$m < 0.1$	–0.002	–0.012
5	$n = \frac{R^2 - Ro'^2}{R^2}$	$n < 0.1$	–0.001	–0.006
6	$R_m = R^2 \times (1 - \sqrt{\lvert R^2 - Ro^2 \rvert})$	$0.5 < R_m$	0.954	0.863
where	$Ro^2 = 1 - \frac{\sum_{i=1}^{n}(t_i - h_i^o)^2}{\sum_{i=1}^{n}(t_i-\overline{t_i})^2}$, $h_i^o = k \times t_i$		0.997	0.976
	$Ro'^2 = 1 - \frac{\sum_{i=1}^{n}(h_i - t_i^o)^2}{\sum_{i=1}^{n}(h_i-\overline{h_i})^2}$, $t_i^o = k' \times h_i$		0.996	0.971

h_i: Actual output value for the i^{th} output; t_i: Predicted output value for the i^{th} output; $\overline{h_i}$: Average of actual outputs; $\overline{t_i}$: Average of predicted outputs; n: Number of sample.

comparison of the predictions made by these models is also visualized in Fig. 10. The FEM-based equations used to generate independent predictions of the uplift capacity are summarized in (Rahman *et al.* 2001). It can be observed from Table 6 and Fig. 10 that the proposed GP/SA solution has a better generalization capability than the FEM, ANN, NGN and EPR models. The MAE value of the GP/SA model is slightly higher than that of the FEM-based solution.

The task faced by GP/SA and other GP-based approaches is mainly the same as that faced by the ANN-based methods. GP and ANNs are machine learning techniques that can effectively be applied to the classification and approximation problems. They directly learn from raw experimental (or field) data presented to them in order to extract the subtle functional relationships among the data, even if the underlying relationships are unknown or the physical meaning is difficult to be explained. Contrary to these methods, most conventional empirical and statistical methods like FEM need prior knowledge about the nature of the relationships among the data. Classical constitutive models rely on assuming the structure of the model in advance, which may be suboptimal. Therefore, the GP and ANN-based approaches are well-suited to modeling the complex behavior of most geotechnical engineering problems with extreme variability in their nature (Shahin 2009). In spite of similarities, there are some important differences between GP and ANNs. ANNs suffer from some shortcomings including lack of transparency and knowledge extraction. That is, they do

Table 6 Performance statistics of the prediction models for the uplift capacity

No.	Reference	L/d	D/L	θ (Rad)	S_u (kPa)	T_k	Q (kPa)	Q_{FEM} (kPa)	Q_{ANN} (kPa)	Q_{NGN} (kPa)	Q_{EPR} (kPa)	Q_{LSR} (kPa)	$Q_{\mathrm{Traditional\ GP}}$ (kPa)	$Q_{\mathrm{GP/SA}}$ (kPa)
1	Singh *et al.* (1996)	0.75	0	$\pi/2$	6	4E-02	21.5	18	21.4	11.9	32.2	20.4	18.2	27.5
2	Rao *et al.* (1997)	1	0	$\pi/2$	1.8	1E-04	11.1	12.3	21.3	52.2	15.4	21.3	11.8	9.5
3	Rao *et al.* (1997)	2	0	$\pi/2$	2.6	1E-04	21.9	49	27.6	48.4	19.4	17.6	21.5	26.2
4	Rao *et al.* (1997)	2	0	$\pi/2$	3.6	1E-04	33.6	49.6	33.7	53.1	26.4	25.9	29.9	36.1
5	Rao *et al.* (1997)	2	0	$\pi/2$	5.8	1E-04	46.4	50.9	48.8	65.5	42.7	44.2	48.8	57.5
6	Rao *et al.* (1997)	1.5	0	$\pi/2$	5.8	1E-04	38.1	47.5	45.7	75.7	44.8	49.4	43.6	47.7
7	Hogervorst (1980)	1.32	0	0	38	1E-04	134.9	132.5	94.2	131.7	128.2	174.0	103.6	140.8
8	Hogervorst (1980)	1.32	0	0	38	1E-04	133.1	132.5	94.2	131.7	128.2	174.0	103.6	140.8
9	Hogervorst (1980)	1.84	0	$\pi/2$	15.8	1E-04	154.3	161.5	157.3	135.3	149.0	143.8	148.5	143.2
10	Randolph *et al.* (1998)	2.31	0.68	$11\pi/180$	21.6	1E-04	370.4	351	367.1	256.7	326.5	249.9	322.0	342.1
11	El-Gharbawy and Olson (1998)	4	0.47	$5\pi/12$	5.2	1E-05	48.1	46	57.2	138.7	70.9	160.5	92.7	55.8
							R^2	0.992	0.971	0.851	0.991	0.759	0.965	0.995
							MSE	141.04	315.68	2377.16	254.50	2637.39	571.07	123.71
							MAE	8.49	11.01	34.66	10.81	33.55	15.97	8.72

not explicitly explain the underlying physical processes. The knowledge extracted by ANNs is stored in a set of weights that cannot properly be interpreted. Due to the large complexity of the network structure, ANNs do not give a transparent function relating the inputs to the corresponding outputs. The main advantage of GP over ANNs is that GP generates a transparent and structured representation of the system being studied. An additional advantage of GP over ANNs is that determining the ANN architecture is a difficult task. The structure and network parameters of ANNs (*e.g.* number of inputs, transfer functions, number of hidden layers and their number of nodes, etc.) should be identified a priori, which is usually done through a time consuming trial and error procedure. In GP, the number and combination of terms are automatically evolved during model calibration (Shahin 2009, Javadi and Rezania 2009). A notable limitation of GP and its variants is that these methods are parameter sensitive. The performance of the GP/SA algorithm can be improved by using any form of optimally controlling the parameters of the run (*e.g.*, GAs).

However, one of the goals of introducing the expert systems, such as the GP-based approaches, into the design processes is better handling of the information in the pre-design phase. In the initial steps of design, information about the features and properties of targeted output or process are often imprecise and incomplete (Kraslawski *et al.* 1999). Nevertheless, it is idealistic to have some initial estimates of the outcome before performing any extensive laboratory or field work. The GP/SA approaches employed in this research are based on the data alone to determine the structure and parameters of the models. Thus, the derived models can particularly be valuable in the preliminary design stages. For more reliability, the results of the GP/SA-based analyses are suggested to be treated as a complement to conventional computing techniques. In any case, the importance of engineering judgment in interpretation of the obtained results should not be underestimated. In order to develop a sophisticated prediction tool, GP/SA can be combined with advanced deterministic geomechanical models. Assuming the geomechanical model captures the key physical mechanisms, it needs appropriate initial conditions and carefully calibrated parameters to make accurate predictions.

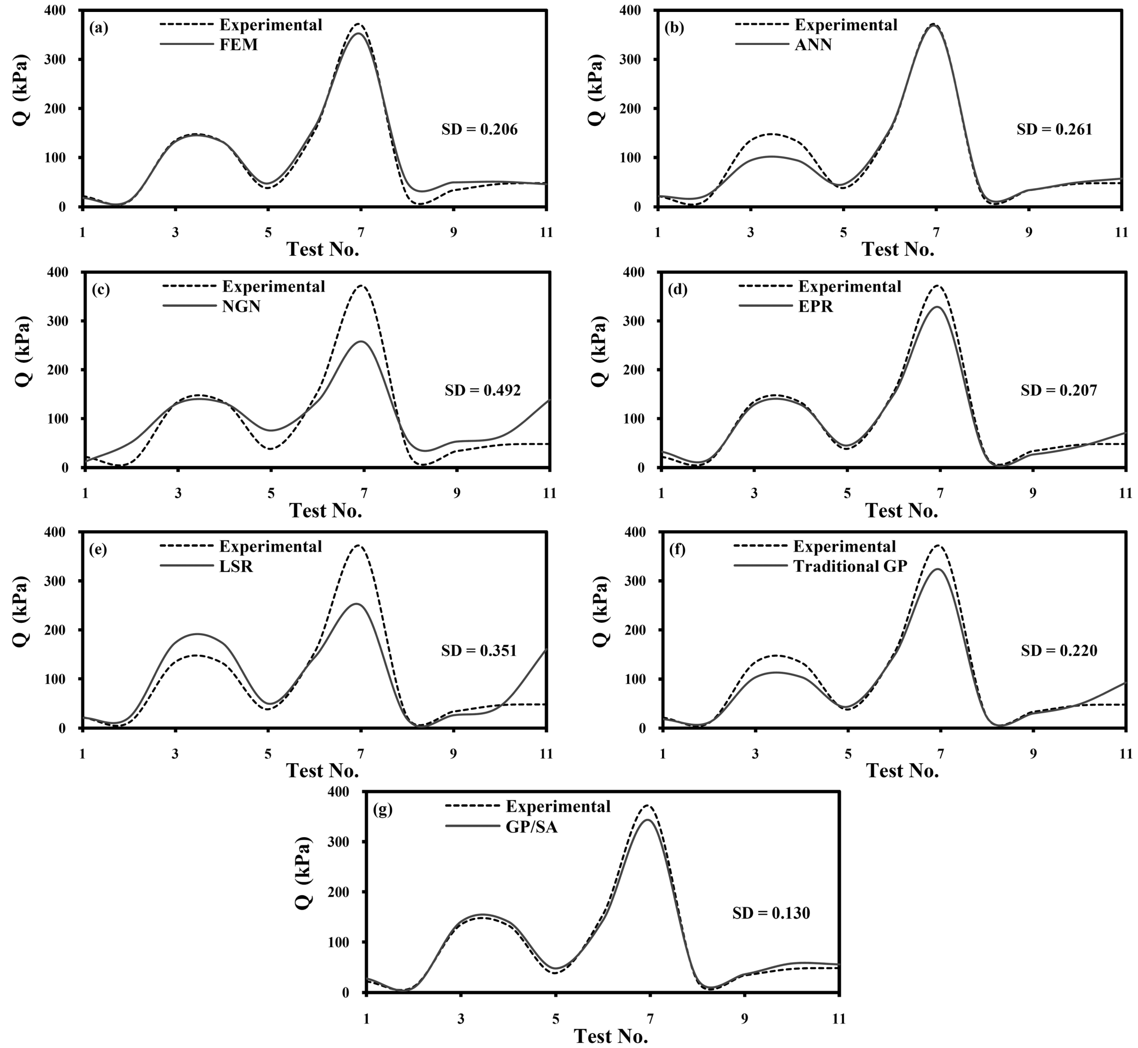


Fig. 10 A comparison of the uplift capacity predictions made by different models (Note: SD = Standard Deviation)

An idea could be to calibrate the geomechanical parameters by the use of GP/SA which takes into account historic data sets as well as the laboratory or field test results. This allows integrating the uncertainties related to in-situ conditions which the geomechanical model does not explicitly account for. GP/SA provides a structured representation for the constitutive material model that can readily be incorporated into the finite element or finite difference analyses. In this case, it is possible to use a suitably trained GP-based material model instead of a conventional (analytical) constitutive model in a numerical analysis tool such as finite element code or finite difference software (like FLAC). It is notable that the numerical implementation of ANNs in the finite element analyses has already been presented by several researchers (*e.g.*, Javadi *et al.* 2005). This strategy has led to some qualitative improvement in the application of finite element method in engineering practice (Javadi and Rezania 2009).

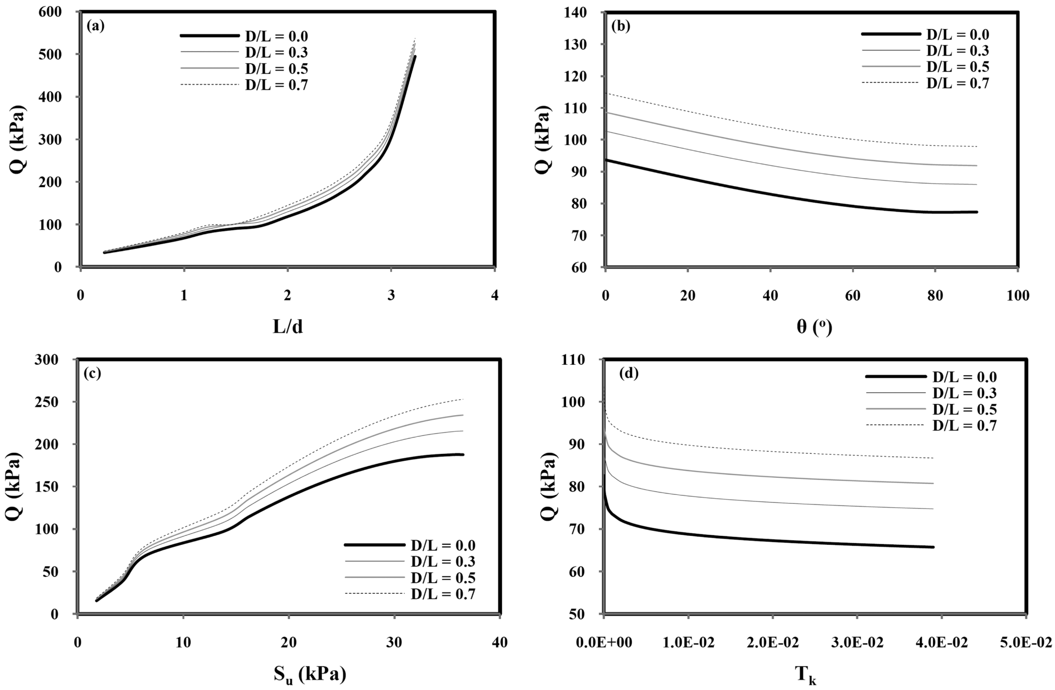


Fig. 11 Contributions of the input parameters in the GP/SA model

6. Sensitivity analysis

Sensitivity analysis is of utmost concern for selecting the important predictor variables. The contributions the input parameters were evaluated through a sensitivity analysis. For this aim, frequency values of the variables were obtained. A frequency value equal to 1.00 for an input indicates that this variable has been appeared in 100% of the best thirty programs evolved by GP/SA. This is a common methodology for the sensitivity analysis in the GP-based studies (Francone 2001, Alavi *et al.* 2010a). The frequency values of the input parameters are presented in Fig. 11. According to these results, the uplift capacity of suction caissons is more dependent on L/d and S_u compared with D/L, θ and T_k. The lower sensitivity of the uplift capacity to D/L and θ may be due to the poor distribution of the data for these variables.

The sensitivity analysis results are expected cases from the geomechanical viewpoint. L/d determines the likely failure mechanism of a caisson and S_u represents the soil resistance. There are earlier findings for the uplift capacity that are in agreement with this observation (Rahman *et al.* 2001).

7. Parametric analysis

For further verification of the proposed GP/SA model, a parametric analysis was performed in this study. The parametric analysis investigates the response of the predicted uplift capacity from the GP/SA model to a set of hypothetical input data. The methodology is based on the change of only one predictor variable at a time while the other variables are kept constant at the average values of

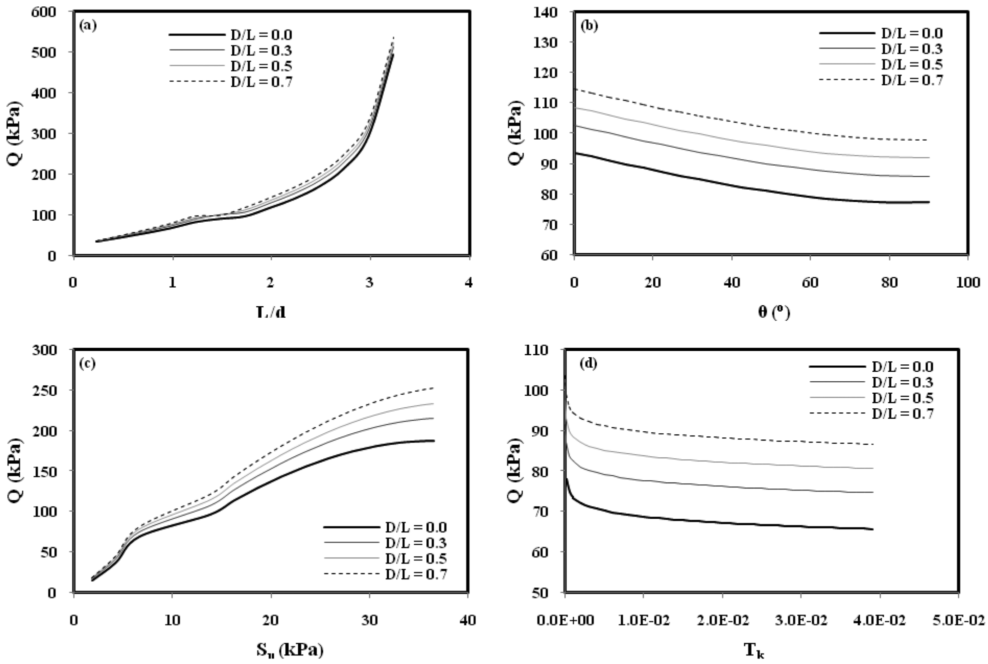


Fig. 12 Parametric analysis of the uplift capacity in the GP/SA model

their entire data sets. These variables are presented to the prediction equation and the uplift capacity is calculated. This procedure is repeated using another variable until the model response is tested for all predictor variables. Figs. 12(a)-(f) present the tendency of the uplift capacity predictions to the variations of L/d, θ, S_u, T_k, and D/L.

The results of the parametric analysis indicate that increases in L/d cause amplification in the uplift capacity. This is mainly due to the additional skin friction and passive resistance acting on the extended portion of the embedment length of the caisson (Rao *et al.* 2006). Deng and Carter (2000) showed that the ultimate load for a suction caisson subjected to vertical uplift loading is positively correlated with L/d. As the load inclination changes from the horizontal to vertical direction, the uplift capacity decreases. It is notable that for $\theta = 0^{\circ}$, the resistance is due to the passive earth pressure of the soil and the skin friction cannot act on the system. For vertical load on caisson ($\theta = 90^{\circ}$), the resistance is only due to the skin friction. Consequently, as the loading direction changes from horizontal to vertical, the resistance component changes from the passive earth pressure to the skin friction (Rao *et al.* 2006). Rao *et al.* (2006) showed that the pullout capacity decreases as the load inclination changes from $\theta = 0^{\circ}$ (horizontal) to $\theta = 90^{\circ}$ (vertical).

As other researchers argued (*e.g.*, Deng and Carter 2000, Rahman *et al.* 2001, Rao *et al.* 2006), the uplift capacity increases when S_u increases (Fig. 12(c)). This is mainly attributed to the improvement of the passive resistance due to the increased soil shear strength. The uplift capacity slightly decreases when T_k increases. The obtained trends seem to be rational since T_k is the ratio of the permeability of the soil to the loading rate at which the caisson is pulled from the ground. Deng and Carter (1999a) found that T_k is negatively related to the uplift capacity. As it is seen in Figs. 12(a)-(d), the uplift capacity increases with the increases in the D/L values. In this context, similar trends were reported by Rahman *et al.* (2001). Also, Deng and Carter (2000) found that the normalized horizontal capacity increases when *D*/*L* increases up to an optimal value equal to 0.63 and thereafter it starts decreasing.

8. Conclusions

In this work, an empirical model was derived for assessing the complex behavior of the uplift capacity of suction caissons by means of the hybrid GP/SA method. Traditional GP and linear regression analyses were performed to have an idea about the predictive power of GP/SA. A reliable database of previously published uplift capacity test results was used for developing the models. The following conclusions may be drawn based on the results presented:

- The developed GP/SA solution gives reliable estimates of the horizontal, vertical and inclined uplift capacity of suction caissons. The validity of the derived model was tested for a part of test results beyond the training data domain. Furthermore, the GP/SA prediction model efficiently satisfies the conditions of different criteria considered for its external validation. The validation phases confirm the efficiency of the model for its general application to the uplift capacity estimation.
- The proposed model produces considerably better outcomes over the traditional GP and regression models. Also, the GP/SA model possesses superiority over the FEM, ANN, NGN, and EPR models. Contrary to the FEM models, the GP/SA-based formulation of the uplift capacity simultaneously handles all different cases (soil drainage conditions, loading rates and loading types).
- Using the derived GP/SA model, the uplift capacity can readily be estimated from the parameters related to the caisson geometry, load attachment point and soil conditions (L/d, D/L, θ, S_u, T_k). Thus, there is no need to go through sophisticated and time-consuming laboratory, centrifugal, or field tests for determining the uplift capacity. The accuracy of the results strongly confirms that L/d, D/L, θ, S_u and T_k can be regarded as efficient representatives of the uplift capacity behavior.
- The straightforward GP/SA model was derived from tests with fairly wide range properties. Thus, it can reliably be used for practical pre-planning and pre-design purposes.
- An expected finding from the results of the sensitivity analysis is that the aspect ratio of the caisson and the undrained shear strength are the most important parameters governing the uplift capacity behavior.
- A general criticism about the GP-based models is that they are only randomly formed functions which are not based on the physical processes. This ambiguity was illuminated by the parametric analysis. The results of the parametric analysis are soundly in agreement with the underlying physical relations governing the behavior of the uplift capacity. This consistency guarantees that the derived GP/SA model is a meaningful combination of the predictor variables.
- The correlation derived using GP/SA is basically different from the conventional constitutive models based on first principles (*e.g.*, elasticity and plasticity theories). One of the distinctive features of GP/SA-based model is that it is based on the experimental data rather than assumptions made in developing the conventional models. Consequently, as more data becomes available, this model can be improved by re-training GP/SA, without repeating the development procedures from the beginning.
- The GP/SA method is particularly practical for the situations where good experimental data are available, the behavior is too complex, or the conventional constitutive models are unable to effectively describe various aspects of the behavior.

Further research can focus on hybridizing GP with other optimization algorithms such as Ant Colony or Tabu Search. Introducing these strategies into the GP process can improve the performance of GP. With regard to the predictor variables, effects of shear strength gradient and anisotropy, surface roughness of skirt, or soil sensitivity (*i.e.* effect of remoulding) may directly be included into the analysis.

References

Alavi, A.H. and Gandomi, A.H. (2010), "A robust data mining approach for formulation of geotechnical engineering systems", *Int. J. Comput. Aided Meth. Eng.-Eng. Computations.* (in press)

Alavi, A.H., Ameri, M., Gandomi, A.H. and Mirzahosseini, M.R. (2010a), "Formulation of flow number of asphalt mixes using a hybrid computational method", *Constr. Build. Mater.*, DOI: 10.1016/j.conbuildmat. 2010.09.010. (in press)

Alavi, A.H., Gandomi, A.H. and Heshmati, A.A.R. (2010b), "Discussion on soft computing approach for real-time estimation of missing wave heights", *Ocean Eng.*, **37**, 1239-1240.

Aubeny, C.P., Han, S.W. and Murff, J.D. (2003), "Suction caisson capacity in anisotropic soil", *Int. J. Geomech.*, **3**(4), 225-235.

Aubeny, C.P., Moon, S.K. and Murff, J.D. (2001), "Lateral undrained resistance of suction caisson anchors", *Int. J. Offshore Polar*, **11**(2), 95-103.

Aubeny, C.P. and Murff, J.D. (2005), "Simplified limit solutions for the capacity of suction anchors under undrained conditions", *Ocean Eng.*, **32**, 864-877.

Banzhaf, W., Nordin, P., Keller, R. and Francone, F. (1998), *Genetic programming - an introduction. on the automatic evolution of computer programs and its application*, dpunkt/Morgan Kaufmann, Heidelberg/San Francisco.

Baykasoglu, A., Gullub, H., Canakcı, H. and Ozbakır, L. (2008), "Prediction of compressive and tensile strength of limestone via genetic programming", *Expert. Syst. Appl.*, **35**(1-2), 111-123.

Brameier, M. and Banzhaf, W. (2001), "A comparison of linear genetic programming and neural networks in medical data mining", *IEEE T. Evolut. Comput.*, **5**(1), 17-26.

Byrne, B.W. and Houlsby, G.T. (2002), "Experimental investigations of response of suction caissons to transient vertical loading", *J. Geotech. Geoenviron. Eng.*, **128**(11), 926-939.

Cabalar, A.F. and Cevik, A. (2009). "Genetic programming-based attenuation relationships: an application of recent earthquakes in Turkey", *Comput. Geosci.*, **35**, 1884-1896.

Cerny, V. (1985), "Thermodynamical approach to the traveling salesman problem: an efficient simulation algorithm", *J. Optimiz. Theory App.*, **45**, 41-52.

Clukey, E.C., Morrison, M.J., Gariner, J. and Corté, J. F. (1995), "The response of suction caissons in normally consolidated clays to cyclic TLP loading conditions", *Proc. Offshore Technology Conf.*, Houston, Texas, U.S.A., OTC 7796, 909-918.

Colliat, J.L. and Dendani, H. (2002), "Girassol: geotechnical design analyses and installation of the suction anchors", *Proc. SUT Int. Conf. Offshore Site Invest. Geotech.,* London, U.K., 26-28.

Conrads, M., Dolezal, O., Francone, F.D. and Nordin, P. (2004), *Discipulus lite^{TM}-fast genetic programming based on AIM learning technology*, Register Machine Learning Technologies Inc., Littleton.

Deng, W. and Carter, J.P. (1999a), "Vertical pullout behaviour of suction caissons", *Research Report*, The University of Sydney, Centre for Geotechnical Research.

Deng, W. and Carter, J.P. (1999b), "Analysis of suction caissons subjected to inclined uplift loading", *Research Report*, The University of Sydney, Centre for Geotechnical Research.

Deng, W. and Carter, J.P. (2000), "Uplift capacity of suction anchors in uniform soils", *Proc. Geol. Eng.*, Melbourne, Australia.

Deng, W. and Carter, J.P. (2002), "A theoretical study of the vertical uplift capacity of suction caissons", *Int. J. Offshore Polar*, **12**(2), 89-97.

Deschaine L.M. (2000), "Using genetic programming to develop a C/C++ simulation model of a waste incinerator science applications", *Draft Technical Report*, International Corp.

Deschaine, L.M., Zafran, F.A., Patel, J.J., Amick, D., Pettit, R., Francone, F.D., Nordin, P., Dilkes, E. and Fausett, L.V. (2000), "Solving the unsolved using machine learning, data mining and knowledge discovery to

model a complex production process", *Proc. Adv. Tech. Sim. Conf.*, Wasington DC, USA.
Dong, W., Hu, Y. and Randolph, M.F. (2008), "Effect of loading rate on the uplift capacity of plate anchors", *Proc. 8th Int. Offshore Polar Eng. Conf.*, Vancouver, BC, Canada.
Dunlop, P. and Smith, S. (2003), "Estimating key characteristics of the concrete delivery and placement process using linear regression analysis", *Civil Eng. Environ. Syst.*, **20**(4), 273-290.
El-gharbawy, S. and Olson, R. (1998), "Pullout capacity of suction caisson foundation for tension leg platforms", *Proc. 8th Int. Offshore Polar Eng. Conf.*, 531-536.
El-gharbawy, S.L., Olson, R.E. and Scott, S.A. (1999), "Suction anchor installations for deep Gulf of Mexico applications", *Proc. Offshore Technology Conf.*, Houston, Texas, USA, OTC 10992, 747-754.
Erbrich, C.T. and Tjelta, T.I. (1999), "Installation of bucket foundations and suction caissons in sand - Geotechnical performance", *Proc. Offshore Technology Conf.*, Houston, Texas, USA, OTC 10990, 725-735.
Folino, G., Pizzuti, C. and Spezzano, G. (2000), "Genetic programming and simulated annealing: a hybrid method to evolve decision trees", *Proc. EuroGP'2000*, 1802, 294-303.
Francone, F.D. and Deschaine, L.M. (2004), "Extending the boundaries of design optimization by integrating fast optimization techniques with machine-code-based, linear genetic programming", *J. Inf. Sci.*, **161**, 99-120.
Francone, F.D. (2001), *DiscipulusTM software owner's manual*, Littleton, CO, USA, Machine Learning Technologies Inc.
Francone, F.D. (2004), *Discipulus LiteTM software owner's manual*, Littleton, CO, USA, Machine Learning Technologies Inc.
Frank, I.E. and Todeschini, R. (1994), *The data analysis handbook*, Amsterdam, Elsevier, The Nederland.
Fuglsang, L.D. and Steensen-Bach, J.O. (1991), "Breackout resistance of suction piles in clay", *Proc. of Int. Conf.: Centrifuge 91*, Rotterdam, The Netherlands, 153-259.
Gandomi, A.H., Alavi, A.H., Mirzahosseini, R. and Moqaddas Nezhad, F. (2010), "Nonlinear genetic-based models for prediction of flow number of asphalt mixtures", *J. Mater. Civil Eng. - ASCE*, DOI: 10.1061/(ASCE)MT.1943-5533.0000154. (in press)
Golbraikh, A. and Tropsha, A. (2002), "Beware of q^2", *J. Mole. Graph. Model.*, **20**, 269-276.
Hogervorst, J.R. (1980), "Field trials with large diameter suction piles", *Proc. Offshore Technology Conf.*, Houston, Texas, U.S.A., OTC 3817, 217-224.
Javadi, A.A. and Rezania, M. (2009), "Applications of artificial intelligence and data mining techniques in soil modeling", *Geomech. Eng.*, **1**(1), 53-74.
Javadi, A.A., Rezania, M. and Mousavi Nezhad, M. (2006), "Evaluation of liquefaction induced lateral displacements using genetic programming", *Comput. Geotech.*, **33**(4-5), 222-233.
Javadi, A.A., Tan, T.P. and Elkassas, A.S.I. (2005), "Intelligent finite element method", *In the 3rd MIT Conference on Computational Fluid and Solid Mechanics*, Cambridge, Massachusetts, USA.
Johari, A., Habibagahi, G. and Ghahramani, A. (2006), "Prediction of soil-water characteristic curve using genetic programming", *J. Geotech. Geoenviron. Eng.*, **132**(5), 661-665.
Kasabov, N.K. (1998), *Foundations of neural networks fuzzy systems and knowledge engineering*, MIT Press.
Kayadelen, C., Günaydýn, O., Fener, M., Demir, A. and Özvan, A. (2009), "Modeling of the angle of shearing resistance of soils using soft computing systems", *Expert. Syst. Appl.*, **36**, 11814-1126.
Keaveny, J.V., Hansen, S.B., Madshus, C. and Dyvik, R. (1994), "Horizontal capacity of large-scale model anchors", *Proc. 13th Int. Conf. Soil Mech. Found. Eng.*, **2**, 677-680.
Kirkpatrick, S., Gelatt, C.D. and Vecchi, M.P. (1983), "Optimisation by simulated annealing", *Science,* **220**(4598), 671-680.
Koza, J.R. (1992), *Genetic programming: on the programming of computers by means of natural selection*, MIT Press, Cambridge (MA).
Kraslawski, A., Pedrycz, W. and Nyström, L. (1999), "Fuzzy neural network as instance generator for case-based reasoning system: an example of selection of heat exchange equipment in mixing", *Neural Comput. Appl.*, **8**(2), 106-113.
Larsen, P. (1989). "Suction anchors as an anchoring system for floating offshore constructions", *Proc. Offshore Technology Conf.*, OTC 6209, 535-540.
Levasseur, S., Malécot, Y., Boulon, M. and Flavigny, E. (2009), "Statistical inverse analysis based on genetic algorithm and principal component analysis: Method and developments using synthetic data", *Int. J. Numer.*

Anal. Met., **33**(12), 1485-1511.
Li, S., Shangguan Z., Duan, H., Liu, Y. and Luan M. (2009), “Searching for critical failure surface in slope stability analysis by using hybrid Genetic algorithm”, *Geomech. Eng.*, **1**(1), 85-96.
Maniar, D.R. (2000), “A computational procedure for simulation of suction caisson behavior under axial and inclined loads”, *Ph.D. Dissertation*, The University of Texas at Austin.
Maravall, A. and Gomez, V. (2004), *Eviews software, Version5*, Quantitative Micro Software, LLC, Irvine CA.
McCombie, P. and Wilkinson, P. (2002). “The use of the simple genetic algorithm in finding the critical factor of safety in slope stability analysis”, *Comput. Geotech.*, **29**(8), 699-714.
Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H. and Teller, E. (1953), “Equation of State Calculations by Fast Computing Mechanics”, *J. Chem. Phy.*, **21**(6), 1087-1092.
Pai, V.G.A. (2005), “Prediction of uplift capacity of suction caissons using a neuro-genetic network”, *Eng. Computer*, **21**, 129-139.
Poli, R., Langdon, W.B., McPhee, N.F. and Koza, J.R. (2007), “Genetic programming: an introductory tutorial and a survey of techniques and applications”, *Technical report* [CES-475], UK: University of Essex.
Rahman, M.S., Wang, J., Deng, W. and Carter, J.P. (2001), “A neural network model for the uplift capacity of suction caissons”, *Comput. Geotech.*, **28**, 269-287.
Randolph, M.F, O’neill, M.P. and Stewart, D.P. (1998), “Performance of suction anchors in finegrained calcareous soils”, *Proc. Offshore Technology Conf.*, Houston, Texas, USA, OTC 8831, 521-529.
Randolph, M.F. and Houlsby, G.T. (1984), “The limiting pressure on a circular pile loaded laterally in cohesive soil”, *Geotechnique*, **34**(4), 613-623.
Rao, S.N., Latha, K.H., Pallavi, B. and Surendran, S. (2006), “Studies on pullout capacity of anchors in marine clays for mooring systems”, *Appl. Ocean Res.*, **28**, 103-111.
Rao, S.N., Ravi, R. and Prasad, B.S. (1997), “Pullout behaviour of suction anchors in soft marine clays”, *Mar. Georesour. Geotec.*, **1**(15), 95-114.
Rezania, M. and Javadi, A.A. (2007), “A new genetic programming model for predicting settlement of shallow foundations”, *Can. Geotech. J.*, **44**(12), 1462-1473.
Rezania, M., Javadi, A.A. and Giustolisi, O. (2008), “An evolutionary-based data mining technique for assessment of civil engineering systems”, *Eng. Computation.*, **25**(6), 500-517.
Roy, P.P. and Roy, K. (2008), “On some aspects of variable selection for partial least squares regression models”, *QSAR Comb. Sci.*, **27**, 302-313.
Ryan, T.P. (1997), *Modern regression methods*, New York (NY), Wiley.
Senpere, D. and Auvergne, G.A. (1982), “Suction anchor piles - a proven alternative to driving or drilling”, *Proc. Offshore Technology Conf.*, Houston, Texas, U.S.A., OTC 4206, 483-493.
Shahin, M.A., Jaksa, M.B. and Maier, H.R. (2009), “Recent advances and future challenges for artificial neural systems in geotechnical engineering applications.” *Adv. Artif. Neur. Syst.*, Article ID 308239.
Silva, S. (2007), *GPLAB, a genetic programming toolbox for MATLAB*, <http://gplab.sourceforge.net>.
Simpson, A.R. and Priest, S.D. (1993), “The application of genetic algorithms to optimisation problems in Geotechnics”, *Comput. Geotech.*, **15**(1), 1-19.
Singh, B., Datta, M. and Gulhati, S.K. (1996), “Pullout behaviour of superpile anchors in soft clay under static loading”, *Mar. Georesour. Geotec.*, **14**, 217-236.
Smith, G.N. (1986), *Probability and statistics in civil engineering*, Collins, London.
Sukumaran, B. and Mccarron, B. (1999), “Total and effective stress analysis of suction caissons for gulf of mexico conditions”, *ASCE G.S.P.*, **88**, 247-260.
Swingler, K. (1996), *Applying neural networks a practical guide*, New York, Academic Press.
Tjelta, T.I. (1995), “Geotechnical experience from the installation of the Europipe jacket with bucket foundations”, *Proc. Offshore Technology Conf.*, Houston, Texas, USA, OTC 7795, 897-908.
Torres, R.S., Falcão, A.X., Gonçalves, M.A., Papa, J.P., Zhang, B., Fan, W. and Fox, E.A. (2009), “A genetic programming framework for content-based image retrieval”, *Pattern Recogn.*, **42**(2), 283-292.
Watson, P.G. and Randolph, M.F. (1997), “Vertical capacity of caisson foundations in calcareous sediments”, *Proc. Int. Soc. Offshore Polar Eng. Conf.*, 152-159.

CC

Appendix A

Table A.1 Experimental database used for the model development

Reference	L/d	D/L	θ (Rad)	S_u (kPa)	T_k	Q (kPa)
Hogervorst (1980)	1.32	0	0	38	1.00E-05	134.9
	1.32	0	0	38	1.00E-05	133.1
	1.32	0.1	0	38	1.00E-05	149
	1.32	0.1	0	38	1.00E-05	145.5
	1.32	0	$\pi/2$	14.3	1.00E-05	144.6
	1.32	0	1.57	14.3	1.00E-05	176.3
	1.32	0	$\pi/2$	14.3	1.00E-05	149.9
	1.84	0	$\pi/2$	15.8	1.00E-05	154.3
	1.84	0	$\pi/2$	15.8	1.00E-05	160.5
	1.84	0	$\pi/2$	11	1.00E-05	105.8
	1.84	0	$\pi/2$	11	1.00E-05	86.4
	1.84	0	$\pi/2$	11	1.00E-05	88.2
	1.84	0	$\pi/2$	11	1.00E-05	92.6
Larsen (1989)	0.23	0.05	0	31	1.00E-05	128.3
	0.23	0	0	24	1.00E-05	72
	0.68	0	0	24	1.00E-05	21.3
El-Gharbawy and Olson (1998)	4	0.47	$5\pi/12$	5.2	1.00E-05	48.1
	4	0.47	$5\pi/12$	5.2	1.00E-05	54.9
	4	0	$\pi/2$	5.2	1.00E-05	48.8
Fuglsang and Steensen-Bach (1991)	2	0	$\pi/2$	9	1.00E-05	90.1
	2	0	$\pi/2$	7	1.00E-05	80.2
	2	0	$\pi/2$	7.5	1.00E-05	70.5
	2	0	$\pi/2$	8.5	1.00E-05	75.3
	2	0	$\pi/2$	8.3	1.00E-05	71.7
	2	0	$\pi/2$	6	1.00E-05	62.7
	2	0	$\pi/2$	6	1.00E-05	66.3
	2	0	$\pi/2$	25	1.00E-05	244.1
	2	0	$\pi/2$	20.5	1.00E-05	209.4
	2	0	$\pi/2$	22.5	1.00E-05	214.9
Fuglsang and Steensen-Bach (1991)	2	0	$\pi/2$	24	1.00E-05	245.3
	2	0	$\pi/2$	22.5	1.00E-05	204.9
	2	0	$\pi/2$	10.5	1.00E-05	90.4
	2	0	$\pi/2$	7.8	1.00E-05	64.5
Keaveny *et al.* (1994)	1.4	0	0	9	1.00E-05	37
	1.4	0.5	0	9	1.00E-05	70.5
	1.4	0.56	$\pi/18$	5.5	1.00E-05	71.8
Singh *et al.* (1996)	0.75	0	$\pi/2$	6	4.00E-02	21.5

Table A.1 Continued

Reference	L/d	D/L	θ (Rad)	S_u (kPa)	T_k	Q (kPa)
Singh *et al.* (1996)	0.75	0	$\pi/2$	6	4.00E-02	21.5
	0.75	0	$\pi/2$	6	4.00E-03	26
	0.75	0	$\pi/2$	6	4.00E-04	31
	0.75	0	$\pi/2$	2.5	4.00E-02	10.1
	0.75	0	$\pi/2$	2.5	4.00E-03	13.2
	0.75	0	$\pi/2$	2.5	4.00E-04	15.7
	1.5	0	$\pi/2$	6	4.00E-02	23
	1.5	0	$\pi/2$	6	4.00E-03	26.6
	1.5	0	$\pi/2$	6	4.00E-04	32.2
Rao *et al.* (1997)	1	0	$\pi/2$	1.8	1.00E-04	11.1
	1	0	$\pi/2$	2.4	1.00E-04	15.2
	1	0	$\pi/2$	3.6	1.00E-04	26.4
	1	0	$\pi/2$	5.8	1.00E-04	35.6
	1.5	0	$\pi/2$	1.8	1.00E-04	12.9
	1.5	0	$\pi/2$	2.4	1.00E-04	18.7
	1.5	0	$\pi/2$	3.6	1.00E-04	28.8
	1.5	0	$\pi/2$	5.8	1.00E-04	38.1
	2	0	$\pi/2$	1.8	1.00E-04	15.6
	2	0	$\pi/2$	2.6	1.00E-04	21.9
	2	0	$\pi/2$	3.6	1.00E-04	33.6
	2	0	$\pi/2$	5.8	1.00E-04	46.4
Watson and Randolph (1997)	0.4	0	$\pi/2$	6.8	1.00E-05	75
	0.7	0	$\pi/2$	13.7	1.00E-05	135
Randolph *et al.* (1998)	0.43	0	$4\pi/9$	4.2	1.00E-05	48.7
	2.31	0.68	$11\pi/180$	21.6	1.00E-05	370.4
	2.31	0.69	$\pi/12$	23.9	1.00E-05	387.2

Appendix B

The optimum GP/SA program can be compiled in any C++ environment. (Note: *v*[0], ..., *v*[4] respectively represent L/d, S_u, T_k, θ, and D/L in their normalized forms shown in Table 2. *f* [0] is the normalized output parameter.)

```
(float v[])
double tmp = 0;
f[1]=f[2]=f[3]=f[4]=f[5]=f[6]=f[7]=0;
f[0]=v[0];
l0: f[1]-=f[0];
l1: f[0]-=f[1];
l2: tmp=f[1]; f[1]=f[0]; f[0]=tmp;
f[0]*=f[1];
l3: f[0]-=-1;
l4: f[1]-=f[0];
f[1]/=f[0];
l5: f[0]-=v[1];
l6: f[0]/=v[0];
l7: f[0]-=2;
l8: f[0]/=v[2];
l9: f[0]*=f[1];
l10: f[1]/=f[0];
tmp=f[1]; f[1]=f[0]; f[0]=tmp;
{ double f[8];
l11: f[0]*=v[3];
l12: f[0]-=0.5;
l13: f[0]-=v[1];
l14: f[0]+=v[4];
l15: f[0]-=f[1];
l16: f[0]*=v[1];
l17: f[0]+=v[4];
l18: f[0]/=2;
l19: f[0]+=v[2];
l20: f[0]*=v[1];
l21: f[0]+=v[1];
l22: f[0]+=f[0];
l23: f[0]*=v[0];
l24:
l25:
return f[0];}
```