A NEW DESIGN EQUATION FOR PREDICTION OF ULTIMATE BEARING CAPACITY OF SHALLOW FOUNDATION ON GRANULAR SOILS

Ehsan SADROSSADAT[a], Fazlollah SOLTANI[a], Seyyed Mohammad MOUSAVI[b],
Seyed Morteza MARANDI[c], Amir H. ALAVI[d]

[a]Department of Civil Engineering, Kerman Graduate University of Technology, Kerman, Iran
[b]Department of Geography and Urban Planning, Science and Research branch,
Islamic Azad University, Tehran, Iran
[c]Department of Civil Engineering, Bahonar University, Kerman, Iran
[d]Department of Civil and Environmental Engineering, Engineering Building,
Michigan State University, East Lansing, MI 48824, USA

Abstract. A major concern in design of structures is to provide precise estimations of ultimate bearing capacity of soil beneath their foundations. Direct determination of the bearing capacity of foundations requires performing expensive and time consuming laboratory tests. To cope with this issue, several numerical models have been presented by researchers. This paper presents the development of a new design equation for the prediction of the ultimate bearing capacity of shallow foundations on granular soils using linear genetic programming (LGP) methodology. The ultimate bearing capacity is formulated in terms of width of footing, footing geometry, depth of footing, unit weight of sand, and angle of shearing resistance. The LGP-based design equation is established using the results of several load tests on real sized foundations presented in the literature. Validity of the model is verified using a part of laboratory data that are not involved in the calibration process. The statistical measures of coefficient of determination, root mean squared error and mean absolute error are used to evaluate the performance of the model. Sensitivity and parametric analyses are conducted and discussed. The proposed model accurately characterizes the ultimate bearing capacity resulting in a very good prediction performance. The LGP model reaches a better prediction performance than the well-known prediction equations for the bearing capacity of shallow foundations.

Keywords: ultimate bearing capacity, shallow foundations, linear genetic programming, granular soils, prediction.

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Introduction

Columns, bearing walls or other bearing members transmit the building loads to foundations. A foundation is the lowest part of a structure which transmits loads to the underlying soil. Considering the depth of construction, the foundations can be classified into two major groups of shallow and deep foundations. A foundation with a depth (D) to width (B) ratio less than or equal to three or four (D/B ≤ 3 or 4) is simply called a "shallow foundation" (Das 1995; Cerato 2005). Fig.1 shows a definition sketch for shallow foundations. In general, any foundation design must meet three essential requirements (Chen, Duan 2000): (1) providing adequate safety against structural failure of the foundation, (2) offering adequate bearing capacity of soil beneath the foundation with a specified safety against ultimate failure, and (3) achieving acceptable total or differential settlements under working loads.

Bearing capacity failure usually occurs in one of the three modes of general shear, local shear, or punching shear failure (Vesic 1973). The ultimate bearing capacity can be defined as the gross pressure at the base of the foundation at which soil fails in shear. Providing a precise estimation of the ultimate bearing capacity of the soil beneath the foundation is crucial for an efficient design.
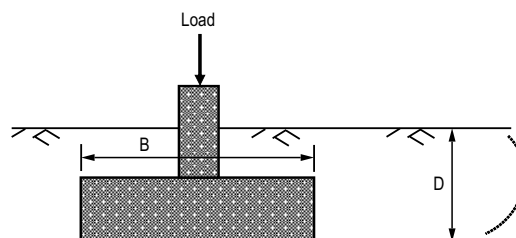

Fig. 1. A typical sketch for shallow foundation

Corresponding author: Amir H. Alavi
E-mail: *ah_alavi@hotmail.com; alavi@msu.edu*

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Four approaches commonly used to determine the bearing capacity of shallow and deep foundations are (Eslami and Gholami 2006): (1) static analysis, (2) in-situ testing methods, (3) full-scale loading tests, and (4) using presumed values recommended by codes and handbooks. Among these approaches, a theoretical solution (i.e. static analysis) is more common.

In this context, Prandtl (1921) and Reissner (1924) presented methods of calculating the ultimate bearing capacity of shallow strip footings based on the plastic theory. Later, the formulation was considerably developed by other researchers over the years (Terzaghi 1943; Taylor 1948; Meyerhof 1963; Hansen 1968; Vesic 1973; Kalinli *et al.* 2011). Terzaghi (1943) extended the theory of Prandtl (1921) by taking into account the weight of soil by the principle of superposition. Taylor (1948) incorporated the surcharge effect of the overburden soil at the foundation level into the Prandtl's formulation. Meyerhof (1963) extended the Terzaghi's bearing capacity equation by including different shape and depth factors. The Meyerhof' model was later modified by Hansen (1968). Vesic (1973) developed a bearing capacity prediction equation similar to that proposed by Hansen (1968).

Recently, Kalinli *et al.* (2011) improved the Meyerhof formula by using a parallel ant colony optimization algorithm. The improved Meyerhof formula proposed by Kalinli *et al.* (2011) found to be more accurate than the theoretical computation formulas. Some of the general forms of the classical equations are summarized in Table 1. As can be observed from this table, the form of the equations presented by the other researchers remained the same as that of Terzaghi's. After extensive in situ and laboratory tests, Meyerhof (1963), Hansen (1968), Vesic (1973) and several other researchers proposed different shape, depth, inclination, ground, and base factors for the

Table 1. General forms of the classical prediction equations for the bearing capacity of shallow foundations

Reference	Equation
Terzaghi (1943)	$q_{ult} = cN_cs_c + \gamma DN_q + 0.5\gamma BN_\gamma s_\gamma$
Meyerhof (1963)	$q_{ult} = cN_cs_cd_ci_c + \gamma DN_qs_qd_qi_q + 0.5\gamma B.N_\gamma s_\gamma d_\gamma i_\gamma$
Hansen (1970)	$q_{ult} = cN_cs_cd_ci_cg_cb_c + \gamma DN_qs_qd_qi_qg_qb_q + 0.5\gamma B.N_\gamma s_\gamma d_\gamma i_\gamma g_\gamma b_\gamma$
Vesic (1975)	Same as Hansen's equation

Notes: q_{ult}: ultimate unit resistance or bearing capacity of footing; c: cohesion parameter; γ: average effective unit weight of the soil below and around the foundation; B: foundation width; D: embedment depth of foundation; N_c, N_q and N_γ: non-dimensional bearing capacity factors as exponential functions of ϕ; ϕ: soil internal friction angle; s_c, s_q and s_γ: non-dimensional shape factors; i_c, i_d and i_γ: non-dimensional inclination factors; d_c, d_q and d_γ: non-dimensional depth factors; g_c, g_q and g_γ: non-dimensional ground factors (base on slope); b_c, b_q and b_γ: base factors (tilted base).

bearing capacity equations. However, a major drawback of these classical formulations is that some simplifying assumptions are incorporated into their development. Therefore, they do not always provide reliable estimations of the bearing capacity (Cerato 2005; Kalinli *et al.* 2011).

The complexity of analysis of bearing capacity behavior implies the necessity to utilize alternative prediction methods. Numerous computer-aided modeling tools such as soft computing techniques have been proposed by extending developments in computational software and hardware. Artificial neural networks (ANNs) are one of the most popular branches of the soft computing techniques. In recent years, they have been successfully applied to behavioral modeling of many civil engineering problems (Hoła, Schabowicz 2005; Malinowski *et al.* 2006; Kaplinski, Janusz 2006; Schabowicz, Hola 2007; Das, Basudhar 2008; Sonmez, Ontepeli 2009; Dikmen, Sonmez 2011). Recently, Padmini *et al.* (2008) utilized neuro-fuzzy inference system (ANFIS) to predict the ultimate bearing capacity of shallow foundations on cohesionless soils. ANFIS combines the transparent, linguistic representation of a fuzzy system with the learning ability of ANNs. Furthermore, Padmini *et al.* (2008) conducted a comparative study between ANFIS, ANN and fuzzy inference system (FIS) for the prediction of the ultimate bearing capacity. Kuo *et al.* (2009) used ANNs to predict the bearing capacity of strip footing on multi-layered cohesive soil. More recently, Kalinli *et al.* (2011) developed an ANN model to predict the ultimate bearing capacity. Despite the acceptable performance of the ANN-based approaches, they are not capable of producing simplified prediction equations.

Genetic algorithm (GA) is a powerful optimization method based on the principles of genetics and natural selection. GA has been shown to be suitably robust for a wide variety of engineering problems (Baušys, Pankrašovaite 2005; Milani, G., Milani, F. 2008; Šešok, Belevicius 2008; Šešok *et al.* 2010). Genetic programming (GP) (Koza 1992) is a specialization of GA where the solutions are computer programs rather than binary strings (Banzhaf *et al.* 1998). Genetic programming (GP) (Koza 1992) is a new alternative approach to overcome the limitations of ANNs. One of the main features of GP over other soft computing tools (e.g. ANNs, ANFIS, etc.) is its ability to generate simplified prediction equations without assuming prior form of the existing relationship (Alavi *et al.* 2011). For the last decade, GP has been pronounced as a powerful method for simulating the behavior of civil engineering problems (Narendra *et al.* 2006; Javadi *et al.* 2006; Tung *et al.* 2009; Gandomi *et al.* 2011a; Gandomi and Alavi 2011). Linear genetic programming (LGP) (Brameier, Banzhaf 2007) is a new subset of GP. LGP operates on programs that are represented as linear sequences of instructions of an imperative programming language (Brameier, Banzhaf 2001, 2007). In contrast with GA, classical GP and ANNs, ap-

plication of LGP in the field of civil engineering is totally new and original (Gandomi *et al.* 2010; Alavi, Gandomi 2011, 2012).

The paper aims at employing LGP to derive a new design equation for the estimation of the ultimate bearing capacity of shallow foundations. The proposed model relates the bearing capacity to various predictor variables including width of footing, depth of footing, footing geometry, unit weight of sand, and angle of shearing resistance. A database containing 97 load test data is used to calibrate the model.

1. Methodology

Linear genetic programming

GP creates computer programs to solve a problem through simulating the biological evolution of living organisms (Koza 1992). Generally, in GP, inputs and corresponding output data samples are known and the main goal is to find a program that connects them (see Fig. 2) (Weise 2009). Most of the genetic operators used in GA can 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 classical GP solutions are computer programs represented as tree structures and expressed in a functional programming language (such as LISP) (Koza 1992; Alavi *et al.* 2011). In other words, in GP, the evolving programs (individuals) are parse trees than can vary in length throughout the run rather than fixed-length binary strings. The fitness of each program generated by GP is evaluated using a fitness function. Thus, the fitness function is the objective function that GP aims to optimize (Gandomi *et al.* 2011b).

In addition to classical tree-based GP, there are other types of GP where programs are represented in different ways. These are linear and graph-based GP (Banzhaf *et al.* 1998). Recently, several linear variants of GP have been developed such as linear genetic programming (LGP) (Brameier, Banzhaf 2007) and multi-expression programming (MEP) (Oltean, Grosan 2003). The linear variants of GP make a clear distinction between the genotype and phenotype of an individual. In these variants, individuals are represented as linear strings (Oltean, Grosan 2003). There are some main reasons for using linear GP. Computers do not naturally run tree-shaped programs. Therefore, slow interpreters have to be used as a part of classical tree-based GP. Conversely, by evolving the binary bit patterns, the use of an expensive interpreter is avoided. Consequently, a linear GP system can run several orders of magnitude faster than comparable interpreting systems. The enhanced speed of the linear variants of GP (e.g. LGP and MEP) permits conducting many runs in realistic timeframes. This leads to deriving consistent and high-precision models with little customization (Francone, Deschaine 2004; Poli *et al.* 2007; Gandomi *et al.* 2011b).

LGP is a new subset of GP with a linear structure similar to the DNA molecule in biological genomes. In LGP, expressions of a functional programming language (such as LISP) are substituted by programs of an imperative language (such as C/C++) (Brameier, Banzhaf 2001, 2007). Fig. 3 presents a comparison of structure of a program evolved by LGP and classical GP. As shown in this figure, a linear genetic program can be seen as a data flow graph generated by multiple usage of register content. In classical tree-based GP, the data flow is more rigidly determined by the tree structure of the program (Brameier, Banzhaf 2001; Gandomi *et al.* 2011b).

In the LGP system described here, a program is interpreted as a variable-length sequence of simple C instructions. The instruction set or function set of LGP contains arithmetic operations, conditional branches, and function calls. The terminal set of the system is composed of variables and constants. The instructions are restricted to operations that accept a minimum number of constants or memory variables, called registers (f), and assign the result to a destination register, e.g. $f_0 := f_1 + 1$. A part of a linear genetic program in C code is represented in Fig. 4. In this figure, register $f[0]$ holds the final program output (Gandomi *et al.* 2010).

Here are the steps which the LGP system follows for a single run (Brameier, Banzhaf 2007; Gandomi *et al.* 2010):

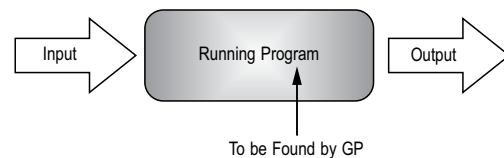1) Initializing a population of randomly generated programs and calculating their fitness values.

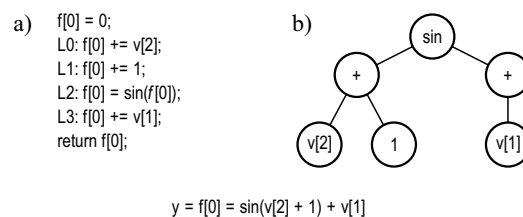Fig. 2. GP in the context of the input-processing-output model

a)
```
f[0] = 0;
L0: f[0] += v[2];
L1: f[0] += 1;
L2: f[0] = sin(f[0]);
L3: f[0] += v[1];
return f[0];
```

b)

y = f[0] = sin(v[2] + 1) + v[1]

Fig. 3. A comparison of a GP program structure evolved by: (a) LGP; (b) Classical tree-based GP (after Gandomi *et al.* 2011b)


```
L0: f[0]–=v[1]
L1: f[0]*=2.5;
L2: f[0]/=v[0];
L3: f[0]+=v[4];
L4: f[0]/=2.5;
L5: f[0]=sin(f[0]);
L6: f[0]+=f[0];
```

Fig. 4. An excerpt of a linear genetic program

2) Running a Tournament. In this step four programs are selected from the population randomly. They are compared based on their fitness. Two programs are then picked as the winners and two as the losers.

3) Transforming the winner programs. After that, two winner programs are copied and transformed probabilistically into two new programs via crossover and mutation operators.

4) Replacing the loser programs in the tournament with the transformed winner programs. The winners of the tournament remain unchanged.

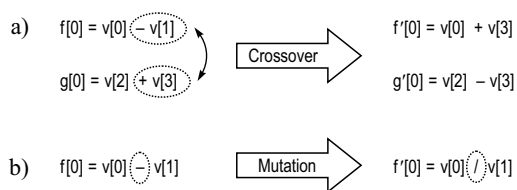5) Repeating steps two through four until termination or convergence conditions are satisfied.

Fig. 5. Typical variation operations in LGP:
(a) crossover and (b) mutation

Crossover occurs between two or more instruction blocks whereas mutation occurs on a single instruction. Fig. 5 demonstrates typical crossover and mutation in LGP. The crossover operation works by exchanging continuous sequences of instructions between parents. As it is seen in Fig. 5(a), a segment of random position and arbitrary length is selected in each of the two parents (f(0) and g(0)) and exchanged. If one of the two children would exceed the maximum length, crossover is aborted and restarted with exchanging equally sized segments (Brameier, Banzhaf 2001; Gandomi *et al.* 2011b). Two commonly used types of standard LGP mutations are micro and macro mutation. The micro mutation changes an operand or an operator of an instruction. The macro mutation operation inserts or deletes a random instruction (Brameier, Banzhaf 2001; Gandomi *et al.* 2011b).

2. Numerical simulation of bearing capacity of shallow foundations

In order to provide reliable estimations of the bearing capacity of shallow foundations, the effect of several parameters should be incorporated into the model development. Considering the basic forms of the existing prediction equations (see Table 1), the bearing capacity of shallow foundations of cohesionless soils mainly depends on the foundation geometry and properties of the soil beneath it (Padmini *et al.* 2008). The most important parameters related to the geometry of the foundation are its width, length of footing, shape (square, rectangular and circular) and depth of embedment. The significant influence of the soil (sand) physical properties such as angle of shearing resistance and the unit weights from above and below the water table on its bearing capacity is well understood (Padmini *et al.* 2008). In the present

study, the LGP approach is employed to develop a new model relating the ultimate bearing capacity of shallow foundations (q_{ult}) and the above mentioned influencing parameters. Consequently, q_{ult} (kPa) is considered to be a function of the following parameters:

$$q_{ult} = f\left(B, D, \frac{L}{B}, \gamma, \phi\right), \qquad (1)$$

where: B (m): width (least lateral dimension) of footing; D (m): depth of footing; L/B: footing geometry; where L is length of footing; γ (kN/m³): unit weight of soil. If the soil is located above the water table, its dry unit weight (γ_d) is used. For the cases where the soil is located below the water table, its effective unit weight (γ') is considered; ϕ (°): angle of shearing resistance.

2.1. Experimental database

A comprehensive database containing 97 experimental test results from 6 independent studies is obtained from the literature to develop the model. The database consists of 47 load tests on large-scale footings and 50 load tests on small-scale model footings. The large-scale test results are reported by Muhs and Weiß (1971), Weiß (1970), Muhs *et al.* (1969), Muhs and Weiß (1973), and Briaud and Gibbens (1999). Gandhi (2003) reported the results of the smaller scale model footings. The ultimate load in large-scale tests is defined as the load corresponding to the point where the slope of the load settlement curve is minimum. For small-scale tests, the ultimate load is defined as the load corresponding to the point of break of the load settlement curve in a log–log plot (Padmini *et al.* 2008). The database includes the results of experiments on square, rectangular and strip footings of different sizes tested in sand beds of various densities. This reliable database has been employed by Padmini *et al.* (2008) and Kalinli *et al.* (2011) to develop ANFIS, ANN and FIS-based prediction models for the ultimate bearing capacity. The descriptive statistics of the test results is given in Table 2. To visualize the distribution of the samples, the data are presented by frequency histograms (Fig. 6). As can observe from Fig. 6, the distributions of the predictor variables are not uniform. The frequency histograms present important information about the density of the samples. For instance, the histogram for D indicates that the samples are generally weighted about 0.1 m (Fig. 6(b)). The LGP model would most probably provide better predictions for such cases where the densities of the variables are higher.

Overfitting is one of the principal problems in generalization of the soft computing methods. 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 individuals from the run on a validation set to find a better generalization (Banzhaf *et al.* 1998). This technique is used herein for improving the generalization of the models. For this purpose, the
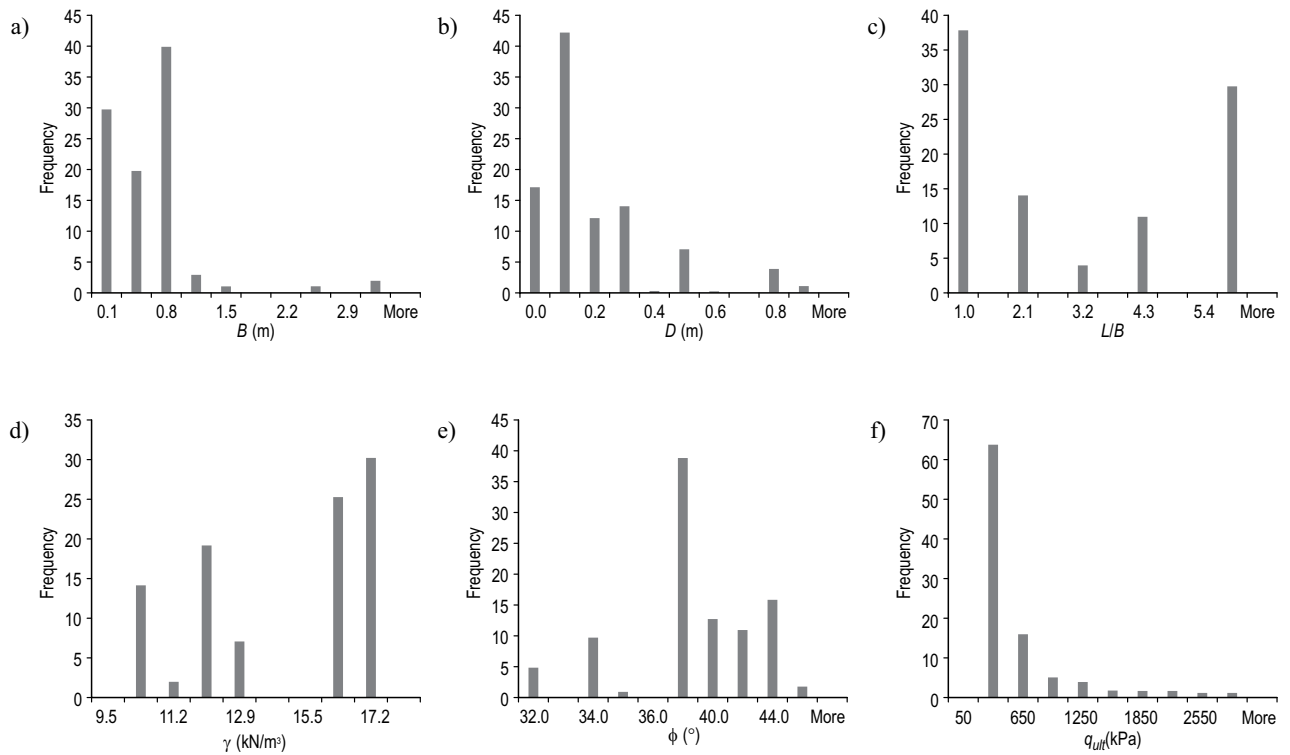
Fig. 6. Histograms of the variables used for the model development

available data sets are randomly divided into three sets: (1) learning, (2) validation, and (3) testing subsets. The learning data are used for the genetic evolution. The validation data are used to specify the generalization capability of the evolved programs on data they did not train on (model selection). In other words, the learning and validation data sets are used to select the best evolved programs and are included in the training process. Thus, they are categorized into one group referred to as training data. Finally, the testing data are used to measure the performance of the models by LGP on data that play no role in building the models (Gandomi *et al.* 2011b). Of the 97 data, 78 data sets are taken as the training data (69 data vectors for the learning process and 9 data vectors

for the validation phase). The remaining 19 sets are used for the testing of the derived models.

2.2. Parameters for measuring performance

The parameters used to evaluate the performance of the models are coefficient of determination (R^2), root mean squared error (RMSE) and mean absolute error (MAE). These parameters are calculated using the following equations:

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)\left(t_i - \overline{t_i}\right)\right)^2}{\sum_{i=1}^{n}\left(h_i - \overline{h_i}\right)^2 \sum_{i=1}^{n}\left(t_i - \overline{t_i}\right)^2}; \qquad (2)$$

Table 2. Descriptive statistics of the variables used for the model development

Parameter	B (m)	D (m)	L/B	γ_d or γ' (kN/m³)	ϕ (°)	q_{ult} (kPa)
Mean	0.40	0.165	3.100	14.18	38.55	439.6
Standard Error	0.05	0.020	0.217	0.266	0.33	53.9
Standard Deviation	0.51	0.200	2.140	2.623	3.27	530.8
Sample Variance	0.26	0.040	4.578	6.880	10.74	281832
Kurtosis	15.3	2.767	−1.62	−1.62	−0.64	6.1
Skewness	3.6	1.774	0.373	−0.355	−0.03	2.46
Range	2.95	0.889	5.0	7.25	12.80	2788.5
Minimum	0.05	0.000	1.0	9.85	32	58.5
Maximum	3.01	0.889	6.0	17.10	44.8	2847

$$\text{RMSE} = \sqrt{\frac{\sum\limits_{i=1}^{n}(h_i - t_i)^2}{n}} \times 100; \qquad (3)$$

$$\text{MAE} = \left[\frac{1}{n}\sum_{i=1}^{n}|h_i - t_i|\right], \qquad (4)$$

where: h_i and t_i are the actual and predicted output values for the ith output, respectively. $\bar{h}_i$ and $\bar{t}_i$ are, respectively, the average of the actual and predicted outputs, and n is the number of samples.

2.3. LGP-Based Prediction Model for Bearing Capacity

The available database is used for establishing the LGP prediction model relating q_{ult} to B, D, L/B, γ, and ϕ. Several runs are conducted to obtain a parameterization of LGP that provided enough robustness and generalization. The LGP parameters are changed for different runs. The parameters are selected on the basis of both previously suggested values (Francone 1998–2004; Baykasoglu et al. 2008; Gandomi et al. 2010) and making several preliminary runs and observing the performance behavior. Three optimal levels are set for the population size (500, 2000 and 3000) and two levels are considered for the crossover and mutation rate (50% and 95%). The success of the LGP algorithm usually increases with increasing the initial and maximum program size parameters. In this case, the complexity of the evolved functions increases and the speed of the algorithm decreases. The initial program size is set to 80 bytes. Two optimal values (128, 256) are considered for the maximum program size as tradeoffs between the running time and the complexity of the evolved solutions. Two values (10, 20) are set for the number of demes. This parameter is related to the way that the population of programs is divided. Note that demes are semi-isolated subpopulations that evolution proceeds faster in them in comparison to a single population of equal size (Brameier, Banzhaf 2007). In this study, four basic arithmetic operators (+, −, ×, /) and basic mathematical functions (√) are utilized to get the optimum LGP models. There are $3 \times 2 \times 2 \times 2 \times 2 = 48$ different combinations of the parameters. All of these parameter combinations are tested and 5 replications for each are carried out. Therefore, the overall number of individual runs is equal to $48 \times 5 = 240$. The termination criterion for each run is based on the number of generations that run has gone without improving. In this study, the number of generations without improvement is set to 600. Each run is observed while in progress for overfitting. For this aim, situations are checked in which the fitness of the samples for the learning of LGP is negatively correlated with the fitness on the validation data sets. To evaluate the fitness of the evolved program, the average of the squared raw errors is used. For the runs showing signs of overfitting, the LGP parameters re pro gressively changed so as to reduce the computational

power available to the LGP algorithm until the observed overfitting is minimized. The resulting run is then accepted as the production run. For the LGP-based analysis, the Discipulus software (Conrads et al. 2004) is used. The best model is chosen on the basis of a multi-objective strategy as follows:

1) Finding the simplest model, although this is not a predominant factor.
2) Providing the best fitness value on the training (learning and validation) set of data.

The best LGP program obtained at the end of training in C++ is given in Appendix A. This program can be run in C++ environment. The resulting code may be linked to the optimizer and compiled or it may be called from the optimization routines (Deschaine 2000). To facilitate the use of the derived code, it is converted into a functional representation by successive replacements of variables starting with the last effective instruction (Oltean and Grossan 2003). The optimal LGP-based formulation of q_{ult} is as follows:

$$q_{ult}(kPa) = \phi\left(\left(\left(\gamma + \phi + \frac{3.95(\phi - 35)^2}{L/B}\right)D^2 + 2.5\big(B(\phi - 35) + 1\big)\right)\right). \qquad (5)$$

The initial population size, crossover rate, mutation rate, and maximum program size for the optimal run are equal to 500, 95%, 50% and 128, respectively. This run took 2 min and 38 s on a Pentium 4 personal computer with 3.00 GHz of processor speed and 1 Gb of memory. Fig. 7 shows a comparison between the experimental and predicted q_{ult} values.

3. Discussion of Model Validity

Smith (1986) suggested the following criteria for evaluating the performance of a model:

– If a model gives correlation coefficient (R) > 0.8 (R^2 > 0.64), a strong correlation exists between the predicted and measured values.

In all cases, the error values (e.g. RMSE and MAE) should be at the minimum. It can be observed from Fig. 7 that the LGP model with high R (R^2) and low RMSE and MAE values is able to predict the target values with an acceptable degree of accuracy. The performance of the model on the training and testing data suggests that it has both good predictive ability and generalization performance. The reliability of the models created by LGP is notably dependant on the amount of data used for the training process (Alavi et al. 2011). In this context, 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. Also, they suggest that considering a higher ratio equal to 5 is safer. In the present study, this ratio is higher and is equal to 97/5 = 19.4. Additionally, new criteria recommended by Golbraikh and Tropsha (2002) are checked for the external validation of the model on the testing data sets. It is suggested that at least one slope of regression lines (k or k') through
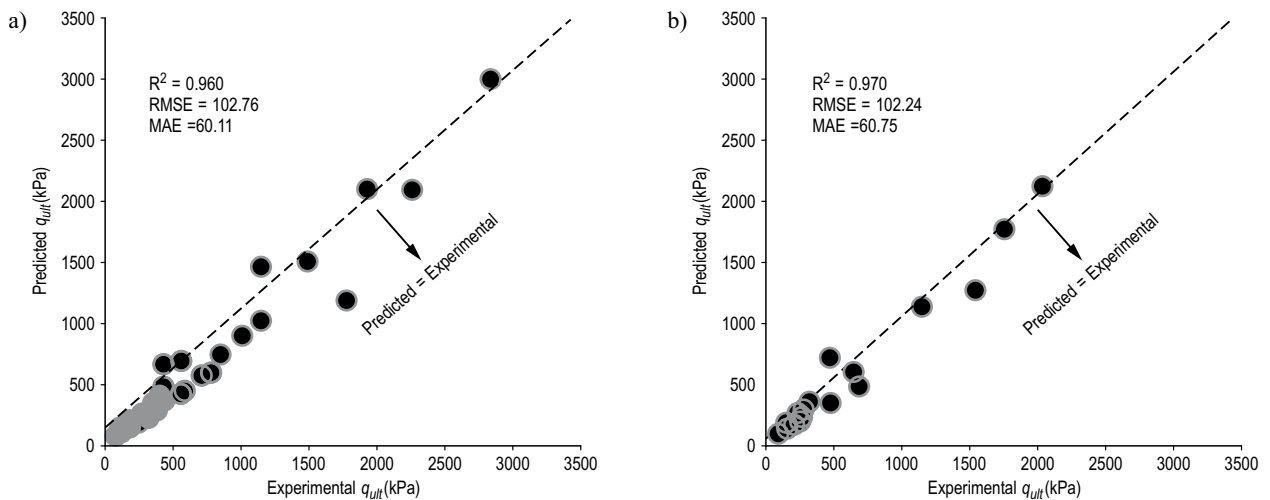
Fig. 7. Experimental versus predicted bearing capacity values using the LGP model: (a) training data, and (b) testing data

the origin should be close to 1. Also, the performance indexes of m and n should be lower than 0.1. Recently, Roy, P. and Roy, K. (2008) introduced a confirming indicator (R_m) for controlling the external predictability of models. 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 considered validation criteria and the relevant results obtained by the models are presented in Table 3. As it is seen in this table, the derived model satisfies all of the required conditions. The validation phase ensures the derived LGP model is strongly valid and it is not established by chance.

In order to have an idea about the predictive power of the LGP model, its performance is compared with that of four traditional models proposed by Terzaghi (1943), Meyerhof (1963), Hansen (1968), and Vesic (1973). Fig. 8 shows a comparison of the predictions made by these models on the testing data sets.

A precise way of observing the systematic mismatches between the predictions and observations is to analyse the residuals, defined as the ratio of the observed to predicted values (Boore, Atkinson 2007). Therefore, in addition to the performance indices described above (i.e. R^2, RMSE and MAE), the values of mean (Mean) of the residuals are also shown in Fig. 8. As can be observed from this figure, the proposed formula signifi-

Table 3. Statistical parameters of the LGP model for the external validation

Item	Formula	Condition	The proposed model
1	R	$0.8 < R$	0.985
2	$k = \dfrac{\sum_{i=1}^{n}(h_i \times t_i)}{h_i^2}$	$0.85 < k < 1.15$	1.015
3	$k' = \dfrac{\sum_{i=1}^{n}(h_i \times t_i)}{t_i^2}$	$0.85 < k' < 1.15$	0.970
4	$m = \dfrac{R^2 - Ro^2}{R^2}$	$\|m\| < 0.1$	−0.030
5	$n = \dfrac{R^2 - Ro'^2}{R^2}$	$\|n\| < 0.1$	−0.029
6	$R_m = R^2\left(1 - \sqrt{\left|R^2 - Ro^2\right|}\right)$	$0.5 < R_m$	0.803
where	$Ro^2 = 1 - \dfrac{\sum_{i=1}^{n}\left(t_i - h_i^o\right)^2}{\sum_{i=1}^{n}\left(t_i - \bar{t}_i\right)^2}$ and $h_i^o = k \times t_i$	Should be close to 1	1.000
	$Ro'^2 = 1 - \dfrac{\sum_{i=1}^{n}\left(h_i - t_i^o\right)^2}{\sum_{i=1}^{n}\left(h_i - \bar{h}_i\right)^2}$ and $t_i^o = k' \times h_i$	Should be close to 1	0.998

cantly outperforms the Terzaghi, Meyerhof, Hansen, and Vesic models. It is worth mentioning that the traditional models are mostly developed using statistical regression techniques. Such models are obtained after controlling only few equations established in advance. Thus, these models cannot efficiently consider the interactions between the dependent and independent variables. On the other hand, LGP introduces completely new features. A major distinction of LGP for determining the bearing capacity lies in its powerful ability to model the mechanical behaviour without requesting a prior form of the existing relationships. The best equation generated by the LGP technique is determined after controlling numerous linear and nonlinear preliminary models. For instance, the proposed design equation is selected among a total of 426,800,992 programs evolved and evaluated by the LGP method during the conducted 240 runs.

Besides, the results obtained by the ANFIS, FIS (Padmini *et al.* 2008) and ANN (Kalinli *et al.* 2011)

models are included in the comparative study. The predictions made by these models on the testing data sets are presented in Fig. 8. Comparing the R^2, RMSE and MAE values for the soft computing tools, it can be seen that the best results are achieved by the ANN model (R^2 = 0.998, RMSE = 29.16, MAE = 10.07) followed by the ANFIS, FIS and LGP solutions. Considering the Mean values, the ANFIS model provides better results than the other models.

Interestingly, in this case, the proposed LGP formulation with a Mean value equal to 1.040 outperforms the ANN (Mean = 1.059) and FIS (Mean = 1.048) models.

Although ANN and ANFIS are successful in prediction, they require the structure of the network (e.g. transfer functions, number of hidden layers and neurons) to be identified in advance. This is usually done through a time consuming trial and error procedure. The knowledge extracted by ANNs is stored in a set of weights that cannot properly be interpreted. ANNs do not give a
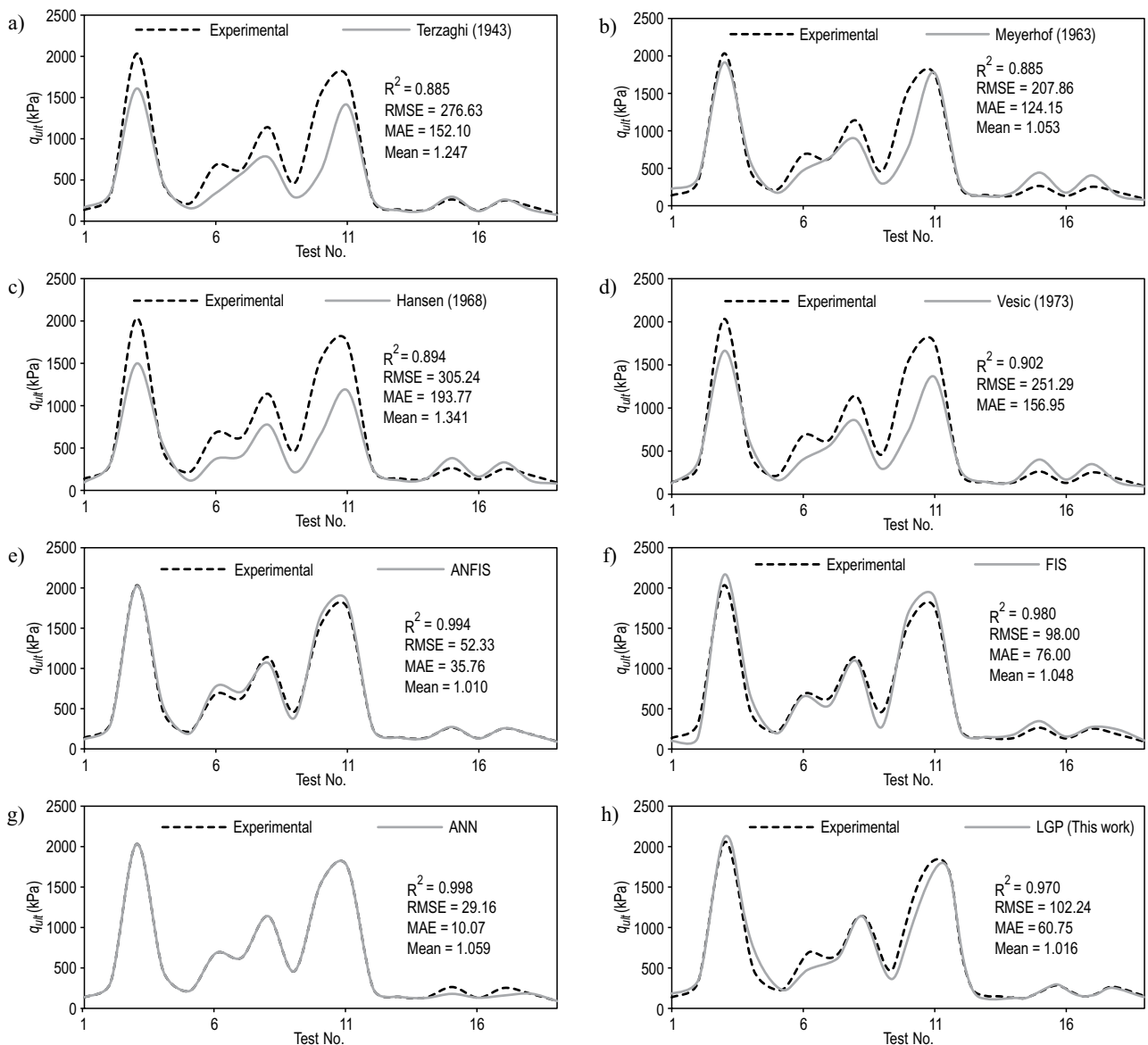

Fig. 8. A comparison of the bearing capacity predictions made by different models

transparent function because of the large complexity of the network structure. The main advantage of LGP over ANN-based approaches is that it generates a transparent and structured representation of the system being studied. Furthermore, LGP can strongly discriminate between the relevant input data and inputs that have no bearing on the solution. ANNs has little capability in this regard and the variable selection is usually an extensive manual job for the researcher (Francone 1998–2004). The explicit nature of FIS may grant its use for prediction purposes. On the other hand, a fundamental disadvantage of FIS is that determination of the fuzzy rules is a difficult task. However, LGP and other soft computing techniques (e.g. ANNs) are based on the data alone to determine the structure and parameters of the model. Thus, the derived model is considered to be mostly valid for use in preliminary design stages and should cautiously be used for final decision-making. The proposed LGP model is suggested to be used to check the general validity of the laboratory or field test results. Further, the proposed model is a good alternative to determine the ultimate bearing capacity of shallow foundations when testing is not possible.

4. Sensitivity and Parametric Analyses

The contributions of the final predictor variables (B, D, L/B, γ, and ϕ) in the LGP model are evaluated through a sensitivity analysis. To perform the sensitivity analysis, frequency values of the input parameters are obtained. A frequency value equal to 100% for an input indicates that this variable has appeared in 100% of the best thirty programs evolved by LGP. This is a common approach in the GP-based analyses (Gandomi *et al.* 2011a, b). The
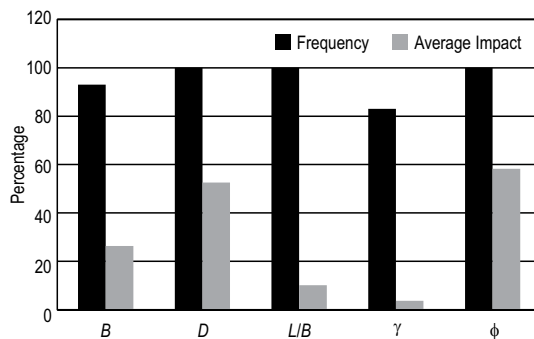
Fig. 9. Contributions of the predictor variables in the LGP analysis

frequency values of the predictor variables are presented in Fig. 8. In addition to frequencies, this figure presents the average impact of removing all instances of each input from the best thirty programs of the project. A value of 100% represents the largest possible impact value. The greater the value is, the more impact its removal has. As can be observed in Fig. 9, all of the predictor variables have very high frequency values. According to this figure, q_{ult} is slightly more sensitive to D, L/B and ϕ than B and γ. Also, the average impact of removing D and ϕ is higher than the other predictor variables. According to Meyerhof (1950) and Padmini *et al.* (2008), D and ϕ have the greatest effects on the bearing capacity than the other properties of the foundation.

Further, a parametric analysis is performed in this study. The parametric analysis investigates the response of the predicted bearing capacity from the LGP model to a set of predictor variables. The methodology is based on
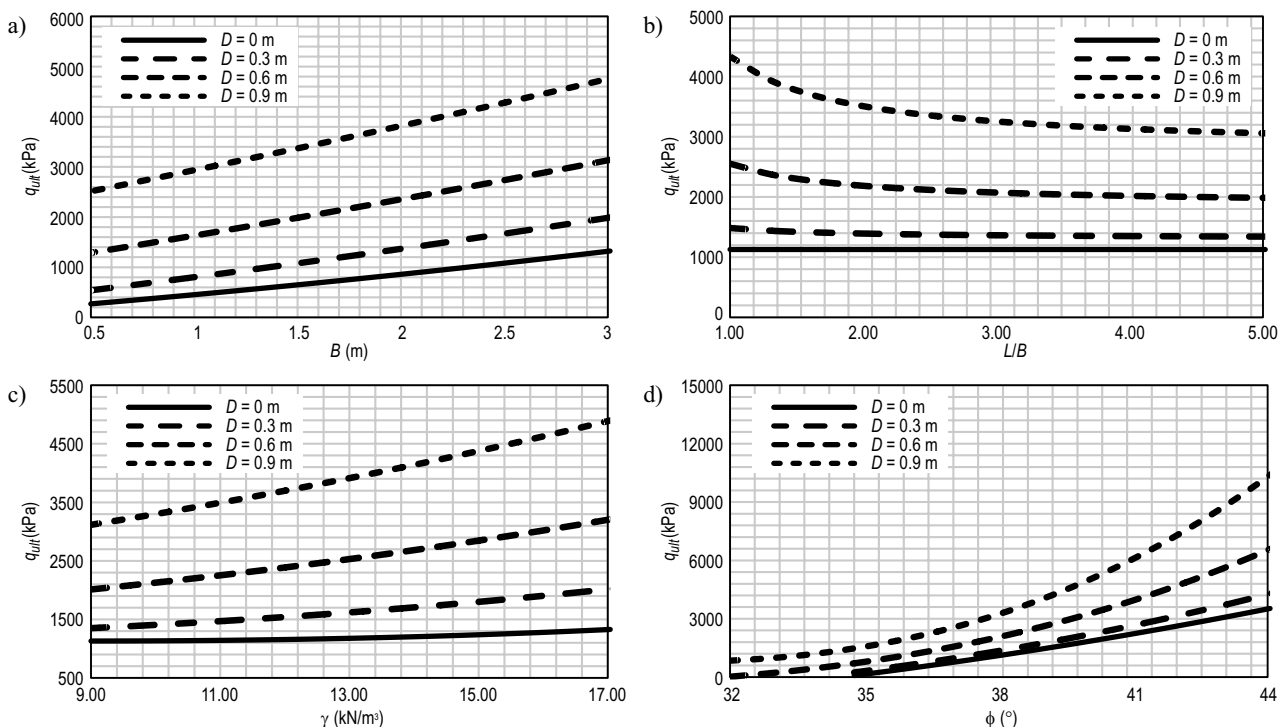
Fig. 10. Parametric analysis of q_{ult} in the LGP model

changing only one predictor variable at a time while the other variables are kept constant at the average values of their entire data sets. A set of synthetic data for the single varied parameter is generated by increasing the value of this in increments. These variables are presented to the prediction equations and q_{ult} is calculated. This procedure is repeated using another variable until the model response is tested for all of the predictor variables (Gandomi *et al.* 2011b). Fig. 10 presents the tendency of the q_{ult} predictions to the variations of the influencing parameters, i.e. *B, D, L/B, γ,* and ф. These design charts indicate that q_{ult} continuously increases with increasing *B, D, γ,* and ф. Further, it can be observed that q_{ult} decreases with increasing *L/B*. Interestingly, all of the plotted trends are soundly expected cases from a geotechnical viewpoint.

Conclusions

In the present study, a new prediction model is derived for the ultimate bearing capacity of shallow foundations using the LGP approach. The proposed model is developed upon several load test results obtained from the literature. The LGP model gives precise estimations of the q_{ult} values. The validation phases confirm the efficiency of the model for its general application to the bearing capacity estimation. The derived model is mostly suitable for pre-design purposes. It may be used as a quick check on solutions developed by more time consuming and in-depth deterministic analyses. The optimal model takes into account the key role of the width of footing, depth of footing, footing geometry, unit weight of sand, and angle of shearing resistance. The proposed model produces considerably better outcomes over the well-known models proposed by Terzaghi (1943), Meyerhof (1963), Hansen (1968), Vesic (1973). The values of the performance indices (R^2, RMSE and MAE) indicate that the LGP model does not outperform the ANFIS, FIS and ANN solutions presented in the literature. Considering the values of mean of the residuals, the LGP model performs superior than the FIS and ANN models. However, a major advantage of LGP over ANFIS, FIS and ANN is that it generates a simple equation which can be easily used for prediction purposes via hand calculations. The predictive capability of the derived model is mostly limited to the range of the data used for its calibration. To cope with this limitation, the model can be easily retrained and improved to make more accurate predictions for a wider range by including the data for other test conditions. The proposed model would probably provide better predictions for the situations where the densities of the data considered for the training of the LGP algorithm are higher. A distinctive feature of the LGP-based model is that it is based on the experimental data rather than on assumptions made in developing the conventional models.

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Appendix A

The optimum LGP program
for the prediction of q_{ult}

The following LGP program can be run in the Discipulus interactive evaluator mode or can be compiled in C++ environment. (Note: v[0], ..., v[4] respectively represent *B, D, L/B, γ,* and ϕ. f[0] holds the output.)

```
float DiscipulusCFunction(float v[])
{long double f[8];
long double tmp = 0;
int cflag = 0;
f[0]=f[1]=f[2]=f[3]=f[4]=f[5]=f[6]=f[7]=0;
L0:        f[0]+=v[0];
L1:        f[0]+=f[0];
L2:        f[1]+=f[0];
L3:        f[0]/=v[0];
L4:        f[0]+=5f;
L5:        f[0]*=-5f;
L6:        f[0]+=v[4];
L7:        f[1]*=f[0];
L8:        f[0]/=v[2];
L9:        f[0]*=f[0];
L10:       f[0]*=v[2];
L11:       f[0]/=0.25f;
L12:       f[0]/=0.449999988079071f;
L13:       f[0]+=v[4];
L17:       f[0]+=v[3];
L18: f[0]*=v[1];
L19:       f[0]*=v[1];
L20:       f[0]+=5f;
L21:       f[0]+=f[1];
L22:       f[0]/=1.5f;
L23:       f[0]+=f[1];
L24:       f[0]/=1.5f;
L25:       f[0]*=v[4];
L26:
if (!_finite(f[0])) f[0]=0;
return f[0];}
```

Ehsan SADROSSADAT. Received his BSc degree in Civil Engineering from Islamic Azad University of Mashhad (IAUM) in 2008, Mashhad, Iran. He is now an MSc student of Geotechnical Engineering in Kerman Graduate University of Technology, Kerman, Iran. He has published about 15 scientific papers in international journals, national conferences. His research interest include applications of artificial intelligence techniques to civil engineering problems, reliability-based design (RBD) in geotechnical engineering, shallow foundations, piles and micro piles, soil improvement (lime and cement), pavement and composite materials.

Fazlollah SOLTANI. Received his BSc degree in Civil Engineering from Sistan and Baloochestan University (Iran) in 1989. In 1994, he received his MSc degree from the Insa de Lyon (France). In 1997, he received his PhD degree from the same university in Geotechnical Engineering. He is a member of teaching faculty in the Civil Engineering Department at Kerman graduate University of Technology (Iran). He has published one book and more than 40 scientific papers in international journals, national and international conferences. His research interest include unsaturated soil permeability, application of geosynthetics in civil engineering, slope stability analysis, liquefaction phenomena, shallow foundation, piles and micro piles.

Seyyed Mohammad MOUSAVI. Received his BSc in Civil Engineering form Sharif University of Technology and MSc degree in Structural Engineering from Taribat Modarres University, Tehran, Iran. He is currently a PhD student of Geography and Urban Planning at Science and Research branch of Islamic Azad University, Tehran, Iran. He has published over 10 papers in international journals, national conferences.His research interests include computer-aided modeling of civil engineering problems, earthquake engineering, and composite materials.

Seyed Morteza MARANDI. Received his BSc degree in Civil Engineering from Texas University in 1978. In 1980, he received his MSc degree from the same University. Immediately after graduating, he returned back home and was employed as a member of teaching faculty at the Civil Engineering Department at Shahid Bahonar University, Kerman, Iran. He received his PhD Degree from University of Leeds in Geotechnical Engineering in 1996. He has published two books and more than 130 scientific papers in international journals, national and international conferences. His research interest include seepage analysis in earth and earth-rock dams, slope stability analysis, liquefaction phenomena, piles and micro piles, application of geo-synthetics in civil engineering, and soil improvement.

Amir H. ALAVI. Graduated in Civil and Geotechnical Engineering from Iran University of Science & Technology (IUST), Tehran, Iran. He used to be a lecturer in Eqbal Lahoori Institute of Higher Education and serve as a researcher in School of Civil Engineering at IUST. He is currently a researcher at the Department of Civil & Environmental Engineering at Michigan State University (MSU), MI, USA. He has over 90 publications in book chapters, indexed journals, and conference proceedings. He has registered two patents and published two books in Elsevier. He is on the editorial board of two journals and serves as a regular reviewer for several indexed journals (Elsevier, Springer, Wiley, Taylor & Francis, etc.). As of October 2013, he has been selected among the Scholar Google 200 Most Cited Authors in Civil Engineering. His current research at MSU is focused on Structural Health Monitoring of Pavement Systems Using Self-Powered Strain Sensors. His research interests include analysis and design using metaheuristic, statistical and probabilistic methods, pavement materials and pavement design, geotechnical engineering, and composite materials.