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The use of neural networks for the prediction of the settlement of pad footings on cohesionless soils based on standard penetration test

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Abstract. In this study, artificial neural networks (ANNs) were used to predict the settlement of pad footings on cohesionless soils based on standard penetration test. To achieve this, a computer programme was developed to calculate the settlement of pad footings from five traditional methods. The footing geometry (length and width), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, Q, and corrected standard penetration test, N_{cor}, varied during the settlement analyses and the settlement value of each footing was calculated for each method. Then, an ANN model was developed for each traditional method to predict the settlement by using the results of the analyses. The settlement values predicted from the ANN model were compared with the settlement values calculated from the traditional method for each method. The predicted values were found to be quite close to the calculated values. It has been demonstrated that the ANN models developed can be used as an accurate and quick tool at the preliminary designing stage of pad footings on cohesionless soils without a need to perform any manual work such as using tables or charts. Sensitivity analyses were also performed to examine the relative importance of the factors affecting settlement prediction. According to the analyses, for each traditional method, N_{cor} is found to be the most important parameter while γ is found to be the least important parameter.

Keywords: artificial neural networks; cohesionless soils; pad footing; settlement; standard penetration test

1. Introduction

Every foundation design requires satisfying the two major criteria: the bearing capacity and the settlement criteria. The settlement criterion is more critical than the bearing capacity criterion in the design of shallow foundations on cohesionless soils. Therefore, settlement criterion usually controls the design process especially when the width of footing exceeds 1 m (Schmertmann 1970). Settlement occurs in cohesionless soils in a short time (i.e., immediately after load application) due to their high degree of permeability (Coduto 1994). Such immediate settlement gives rise to relatively rapid deformation of superstructures, which leads to an inability to remedy damage and to avoid further deformation (Shahin *et al*. 2002). Usually, the settlement of shallow foundations

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for example pad or strip footings are limited to 25 mm (Terzaghi *et al*. 1996).

Artificial neural network (ANN), a branch of the artificial intelligence science, is widely utilized and considered one of the intelligent tools to solve complex problems where the number of affecting parameters is too high and the inter-relationship among them is unknown (Khandelwal and Singh 2009). ANN displays characteristics such as mapping capabilities or pattern association, generalization, robustness or fault tolerance in addition to parallel and high speed information processing (Khandelwal and Singh 2009). ANN learns by examples, thus, it can be trained with known examples of a problem to obtain knowledge about it (Khandelwal and Singh 2009). Once, appropriately trained, the network can be put to effective use of solving unknown or untrained examples of the problem (Khandelwal and Singh 2009). Due to its multidisciplinary nature, ANN is becoming popular among the researchers, planners, designers, etc., as an efficient tool for the accomplishment of their work (Khandelwal and Singh 2009). ANNs have also been applied successfully to many problems in geotechnical engineering due to their remarkable capability.

In this study, ANNs were used to predict the settlement of pad footings on cohesionless soils, without a need to perform any manual work such as using tables or charts. With this purpose in mind, a computer programme (Gul 2011) was developed in the Matlab programming environment to calculate the settlement of pad footings from five traditional settlement prediction methods such as, Meyerhof (1965), Terzaghi and Peck (1967), Pary (1971), Peck *et al*. (1974), and Burland and Burbidge (1985). The footing geometry (length, L, and width, B), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, Q, and corrected standard penetration test, N_{cor} varied during the settlement analyses and the settlement value of each pad footing was calculated for each method by using the written programme. Then, an ANN model was developed for each traditional method to predict the settlement by using the results of the analyses. The settlement values predicted from the ANN model were compared with the settlement values calculated from the traditional method for each method to examine the performance of the prediction capacity of the models developed in the study. Sensitivity analyses were also performed to investigate the relative importance of the factors affecting settlement prediction.

2. Artificial neural networks

Artificial neural networks (ANNs) are a form of artificial intelligence which are based on the biological nervous system and inspired by the structure of biological neural networks and their way of encoding and solving problems (Mohan and Sreeram 2005). An ANN is composed of basically of a large number of highly interconnected processing elements called neurons working in parallel to solve the specific problem. The neural network is first trained by processing a large of input patterns and the corresponding output (Khandelwal and Singh 2009). The neural network is capable to recognize similarities when presented with a new input pattern after proper training and predicting the output pattern (Khandelwal and Singh 2009). Neural networks are also able to detect similarities in inputs, even though a particular input may never have been known previously (Khandelwal and Singh 2009). This property allows its excellent interpolation capabilities, especially when the input data is not definite (Khandelwal and Singh 2009). Neural networks may be used as a direct substitute or an alternative for auto-correlation, multivariable regression, linear regression, trigonometric and other statistical analysis techniques (Singh *et al*. 2004, Khandelwal and Singh 2009).

A network first needs to be trained before interpreting new information (Khandelwal and Singh 2009). A number of algorithms are available for training of neural networks but the back-propagation algorithm is the most versatile and robust technique (Khandelwal and Singh 2009). It provides the most efficient learning procedure for multilayer neural networks (Khandelwal and Singh 2009) Also, the fact that back-propagation algorithms are especially capable of solving predictive problems makes them so popular (Khandelwal and Singh 2009). The description of the structure and operation of ANNs can be found in many publications (e.g., Zurada 1992, Fausett 1994). ANNs architectures are constituted by three or more layers: an input layer, one or more hidden layers, and an output layer. This ANN architecture is commonly named as a fully interconnected feed-forward multi-layer perceptron (MLP). In addition, there is also a bias, which is only connected to the neurons in the hidden and output layers, with modifiable weighted connections. Each neuron in a given layer is joined to all the neurons in the next layer by means of weighted connections. In the input layer, the raw information is presented to the network (Singh *et al*. 2001). Hidden layer or layers process the information taken from the input layer and transfer it to the output layer (Singh *et al*. 2001). The output layer contains the response of the network to the input signals (Singh *et al*. 2001). The number of input and output neurons is the same as the number of input and output variables (Khandelwal and Singh 2009). Number of hidden layers and neurons in the hidden layer change according to the problem to be solved (Khandelwal and Singh 2009).

During training of the network, data is processed through the input layer to hidden layer, until it reaches the output layer (forward pass) (Singh and Verma 2005, Khandelwal and Singh 2009). In this layer, the output is compared to the measured vales (or the "true" output) (Singh and Verma 2005, Khandelwal and Singh 2009). The difference or error between both is propagated back through the network (backward pass) updating the individual weights of the connections and biases of the individual neurons (Singh and Verma 2005, Khandelwal and Singh 2009). The process is repeated for all the training pairs in the data set, until the network error approximates to a threshold defined by a corresponding function; commonly the root mean squared error (RMSE) or summed squared error (SSE) (Singh and Verma 2005, Khandelwal and Singh 2009).

In this study, an ANN model for each traditional method has been modeled for the prediction of the settlement of pad footings. In the ANN models, network training was achieved with the neural network toolbox written in Matlab environment (Math Works 7.0 Inc. 2006) and the Levenberg-Marquardt back-propagation learning algorithm (Demuth *et al*. 2006) was utilized in the training stage. Details of the traditional methods used for estimating the settlement of pad footings, which have produced the data for the ANN models, are presented in the following section.

3. Calculation of settlement of pad footings on cohesionless soils

A computer programme (Gul 2011) was developed in the Matlab programming environment for calculating the settlement, h, of pad footings on cohesionless soils based on standard penetration test from five traditional methods, namely, Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al*. (1974), and Burland and Burbidge (1985). The settlement equations used in the calculations were given in Table 1. In Eqs. (1) to (5) in Table 1, I_c is the compressibility index, q_{net} is the net applied pressure, q_a is the allowable bearing capacity, h_a is the absolute maximum allowable settlement, C_w is the correction for water table depth, α is a constant and taken as 200 in SI units, C_D is the factor for the influence of excavation, C_T is the factor for the thickness of the compressible layer and N_m is the measured average standard penetration value. The footing geometry (length, *L*, and width, *B*), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, *Q*, and corrected standard penetration test, N_{cor} varied during the settlement analyses as follows: The *B* value was varied 1, 2, and 3 m. For each *B* value, the L value was varied as 1, 2, and 3 m. The γ value for each *B–L* pair was varied as 16, 18, 20, and 22 kN/m^3. The D_f value was changed as 0.5 to 3.5 m with step of 1.0 m. The *Q* value was varied from 100 to 1100 kN with step of 200 kN. The N_{cor} value was varied from 5 to 45 with step of 10. Then, the settlement value of each pad footing was calculated for each method by using the written programme. The effect of the water table is already reflected in the measured SPT blow count (Terzaghi and Peck 1967). Thus, the depth of water table is not included in this study. Square and rectangular footings are considered in this study. As found by Burbidge (1982), there is no significant difference between the settlement of circular and square footings having the same width (*B*) on the same soil. Therefore, circular footings are also considered to be equivalent to as square footings. It can be noted from the settlement analysis that the settlement value calculated in each method increases with an increase in the *Q* value, as observed by Ramu and Madaw (2010), and a decrease in the N_{cor} value for the footing having the same geometry, same embedment depth and bulk unit weight. A summary of the results are given in Table 2. It can be noted from Table 2 that Terzaghi and Peck (1967) method generally yielded the highest settlement values; Parry (1971) and Burland and Burbidge (1985) methods yielded lower settlement values; Meyerhof (1965) and Peck *et al*. (1974) generally yielded similar settlement values lower than those predicted by Terzaghi and Peck (1967) and higher than those predicted by Parry (1971) and Burland and Burbidge (1985) methods.

The settlement values calculated from the Terzaghi and Peck (1967) were also compared with those calculated both from the Meyerhof (1965) and Peck *et al*. (1974) methods in Figs. 1 and 2, respectively. It can be seen from Fig. 1 that Terzaghi and Peck (1967) mostly yielded higher settlement values than Meyerhof (1965) method. It can be seen from Fig. 2 that Terzaghi and Peck (1967) generally yielded higher settlement values than Peck *et al*. (1974) methods.

Table 1 Settlement equations of the traditional methods used in this study

Traditional method	Settlement equation	Equation no.
Meyerhof (1965)	$\Delta h = \Delta h_a \dfrac{q_{net}}{q_a}$	(1)
Terzaghi and Peck (1967)	$\Delta h = \dfrac{q_{net}}{q_a} 25$	(2)
Parry (1971)	$\Delta h = \dfrac{\alpha B q_{net}}{N_m} C_D C_T C_w$	(3)
Peck *et al*. (1974)	$\Delta h = \dfrac{q_{net}}{q_a C_w} 25$	(4)
Burland and Burbidge (1985)	$\Delta h = q_{net} B^{0.7} I_c$	(5)

Table 2 A summary of the results

N_{cor}	Q (kN)	D_f (m)	γ (kN/m^3)	B (m)	L (m)	Settlement calculated				
						Meyerhof (1965)	Terzaghi and Peck (1967)	Parry (1971)	Peck *et al.* (1974)	Burland and Burbidge (1985)
5	100	0.5	22	1	2	14.508	23.214	3.776	18.177	4.313
5	300	0.5	16	3	1	34.224	54.762	8.907	42.878	10.174
5	300	2.5	18	1	1	94.860	151.786	44.733	94.860	28.201
5	500	1.5	16	2	1	84.072	134.524	31.947	84.072	24.993
5	900	0.5	22	1	1	330.708	529.167	86.074	414.336	98.315
15	100	0.5	20	1	1	11.160	12.422	2.905	15.909	2.138
15	500	3.5	22	1	2	21.452	23.879	11.672	21.452	4.110
15	700	0.5	18	3	1	27.817	30.964	7.240	39.656	5.329
15	700	2.5	20	2	2	15.500	17.253	10.951	15.500	4.824
15	1100	0.5	22	3	2	21.369	23.787	9.566	24.794	6.650
15	1100	3.5	18	1	3	37.655	41.914	20.488	37.655	7.213
25	300	0.5	16	2	1	10.565	11.489	2.750	17.676	1.650
25	700	2.5	20	1	1	48.360	52.589	22.805	48.360	7.552
25	900	0.5	22	3	1	21.502	23.382	5.596	35.974	3.358
25	1100	1.5	18	2	2	18.451	20.065	10.839	22.037	4.681
35	300	1.5	16	3	3	0.514	0.549	0.387	0.615	0.146
35	300	2.5	22	1	1	13.020	14.079	6.140	13.020	1.777
35	500	1.5	20	2	2	5.049	5.459	2.966	6.258	1.120
35	700	2.5	16	1	3	10.274	11.110	4.845	10.274	1.402
35	700	3.5	22	2	2	5.208	5.632	4.219	5.208	1.155
45	300	0.5	22	3	1	3.679	3.931	0.957	5.067	0.454
45	500	0.5	16	1	1	20.336	21.730	5.293	28.010	2.510
45	500	2.5	18	2	1	8.473	9.054	3.996	8.473	1.046
45	700	0.5	20	3	3	2.902	3.071	1.773	3.440	0.746

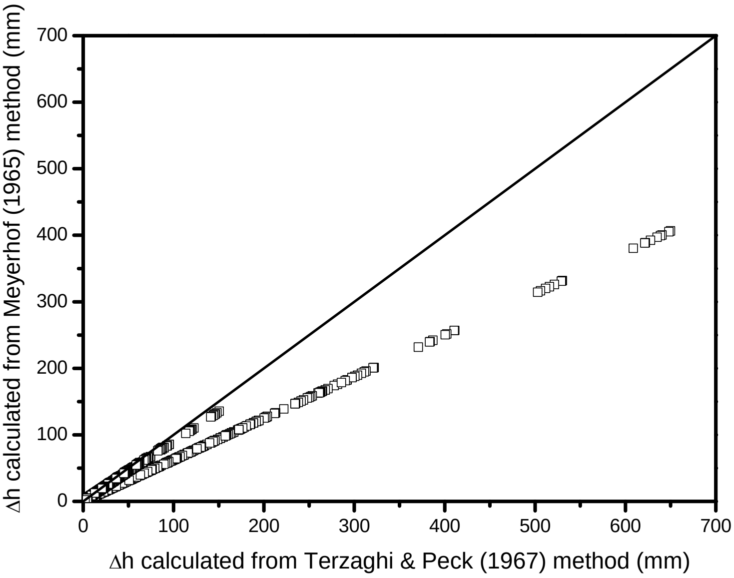


Fig. 1 Comparison of Δh values predicted from Terzaghi and Peck (1967) method with those predicted from Meyerhof (1965) method

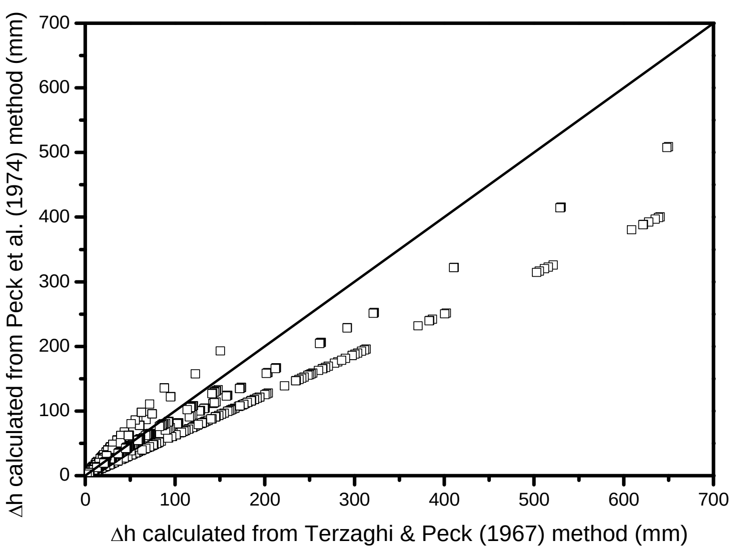


Fig. 2 Comparison of Δh values predicted from Terzaghi and Peck (1967) method with those predicted from Peck *et al*. (1974) method

The settlement values calculated from the Terzaghi and Peck (1967) were compared with those calculated both from the Parry (1971) and Burland and Burbidge (1985) methods in Figs. 3 and 4, respectively. It can be seen from the figures that Terzaghi and Peck (1967) yielded higher settlement values than both the Parry (1971) and Burland and Burbidge (1985) methods.

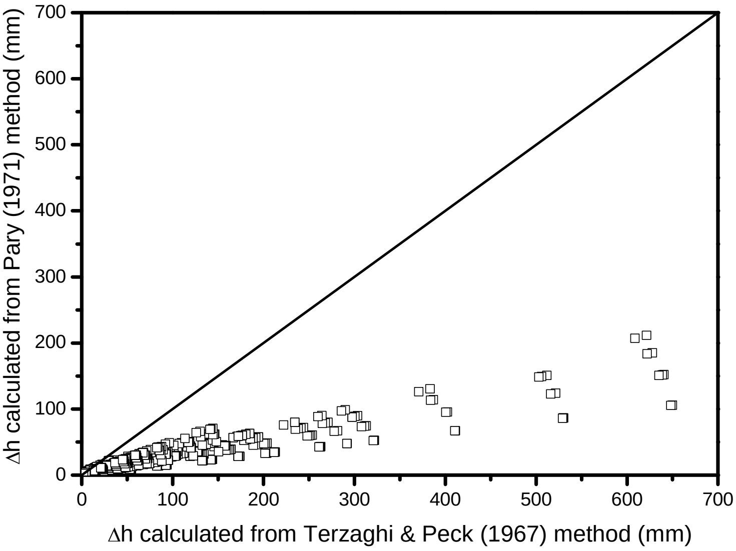


Fig. 3 Comparison of Δ*h* values predicted from Terzaghi and Peck (1967) method with those predicted from Parry (1971) method

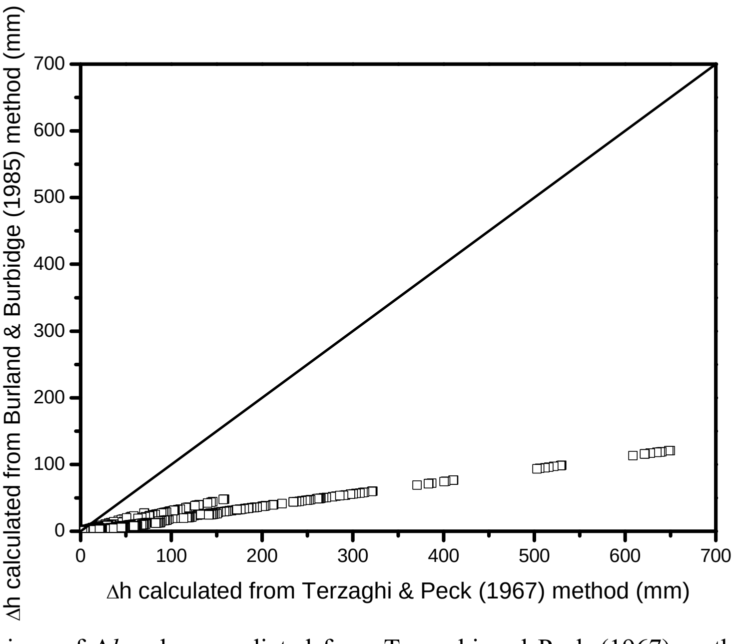


Fig. 4 Comparison of Δ*h* values predicted from Terzaghi and Peck (1967) method with those predicted from Burland and Burbidge (1985) method

The settlement values calculated from the Meyerhof (1965) were compared with those calculated from the Peck *et al*. (1974) in Fig. 5. It can be seen from the figure that Peck *et al*. (1974) yielded slightly higher settlement values than Meyerhof (1965).

The settlement values calculated from the Parry (1971) were compared with those calculated from the Burland and Burbidge (1985) in Fig. 6. It can be seen from the figure that the settlement value calculated from Parry (1971) was mostly higher than Burland and Burbidge (1985).

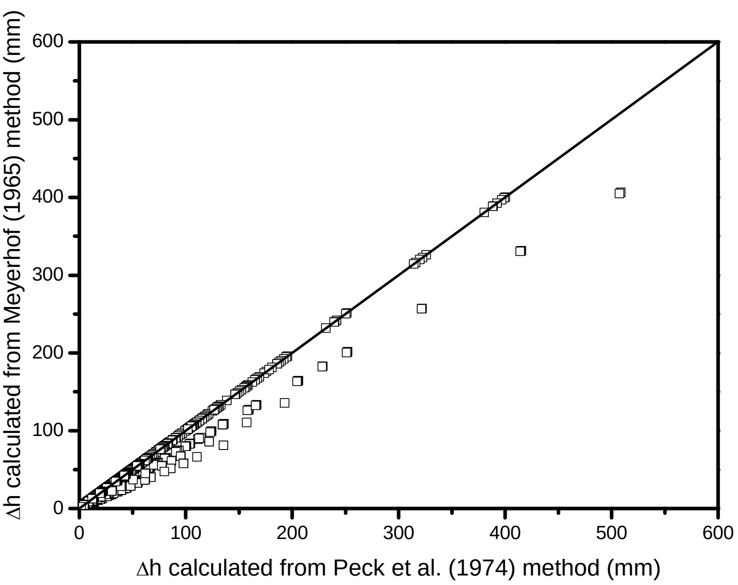


Fig. 5 Comparison of Δh values predicted from Peck *et al*. (1974) method with those predicted from Meyerhof (1965) method

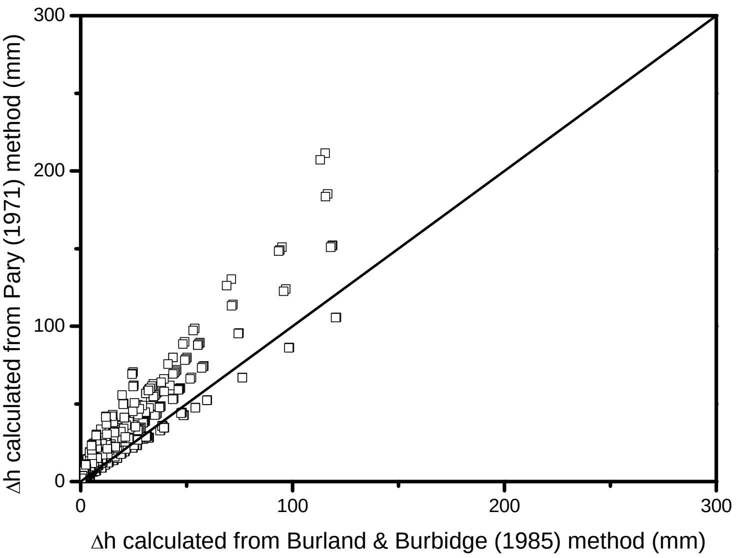


Fig. 6 Comparison of Δh values predicted from Burland and Burbidge (1985) method with those predicted from Parry (1971) method

4. Artificial neural network model

An ANN model for each traditional method is developed to predict the settlement, Δh, value of the pad footing on cohesionless soils. In each ANN model, the input parameters used were the footing geometry (length, L, and width, B), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, Q, and corrected standard penetration test, N_{cor}, while the output parameter was the calculated Δh value. The boundaries of the input and output parameters for each method are given in Table 3. The input and output data were then scaled to lie between 0 and 1, by using Eq. (6). In Eq. (6), where x_{norm} is the normalized value, x is the actual value, $x_{\max}$ is the maximum value and $x_{\min}$ is the minimum value.

$$x_{norm} = \frac{(x - x_{\min})}{(x_{\max} - x_{\min})} \tag{6}$$

It is a common practice to divide the available data into two subsets; a training set and independent validation set, which may cause model over-fitting (Twomey and Smith 1997). Over-fitting occurs mainly because of training of network with too many epochs (Singh and Singh 2005). Over-fitting makes multi-layer perceptrons (MLPs) memorize training patterns in such a way that they cannot generalize well to new data (Choobbasti *et al*. 2009). As a result, crossvalidation technique (Stone 1974), considered to be the most effective method to ensure over-fitting does not occur (Smith 1993), was used as the stopping criterion in this study. In this technique, the database is divided into three subsets: training, validation and testing. The training set is used to adapt the connection weights (Shahin *et al*. 2004). The testing set is utilized to control the performance of the model at various stages of training, and to decide when to stop training to avoid over-fitting (Shahin *et al*. 2004). The validation set is applied to estimate the performance of the trained network in the deployed environment (Shahin *et al*. 2004). Shahin *et al*. (2004) examined the influence of the proportion of the data used in various subsets on the performance of ANN model developed for estimating the settlement of shallow foundations and found no exact relationship between the proportion of the data and model performance. However, they obtained the optimal model performance when 20% of the data were used for validation and the remaining data were divided into 70% for training and 30% for testing. Therefore, in total, 56% of the data (i.e., 2150 data sets) were randomly selected and used for training, 24% (i.e., 922

Table 3 Boundaries of the parameters used for the models developed

	Input parameters						Output parameter				
							Meyerhof (1965)	Terzaghi and Peck (1967)	Parry (1971)	Peck *et al.* (1974)	Burland and Burbidge (1985)
	N_{cor}	Q (kN)	γ (kN/m^3)	D_f (m)	B (m)	L (m)	Δh (mm)	Δh (mm)	Δh (mm)	Δh (mm)	Δh (mm)
Minimum value	5	100	16	0.5	1.0	1.0	0.00	0.00	0.00	0.00	0.00
Maximum value	45	1100	22	3.5	3.0	3.0	406.22	650.00	211.32	508.95	120.77

data sets) for testing, and 20% (i.e., 768 data sets) for validation in each ANN model developed in this study.

The neural network toolbox of MATLAB7.0, a popular numerical computation and visualization software [21], was utilized for training, validation, and testing of MLPs in each ANN model. Firstly, one hidden layer was selected. Caudill (1988) found that ($2I + 1$), (I is the number of input variables), is the upper limit for the number of hidden layer neurons needed to map any continuous function work with I inputs. Therefore, the optimum number of neurons in the hidden layer of the model was decided by varying their number starting with a minimum of 1 then increasing the network size up to ($2I + 1$) in steps by adding 1 neuron each time. Different transfer functions (such as log-sigmoid (Sakellariou and Ferentinou 2005) and tan-sigmoid (Orbanić and Fajdiga 2003) were examined in each ANN model to obtain the best performance in training as well as in testing. Two momentum factors (μ) of 0.01 and 0.001 were chosen for the training process to found for the most efficient ANN architecture in each ANN model.

In each ANN model, network training was achieved with the neural network toolbox written in Matlab environment (Math Works 7.0 Inc. 2006) as follows. Utilizing the random values representing each variable, a random set of weights was initially selected to the connections between the layers. The first output of the network was decided using these weights. The obtained output was then compared with actual output and the mean square error was calculated. The Levenberg-Marquardt back-propagation learning algorithm (Demuth *et al*. 2006) then minimized this error. A feed forward back-propagation ANN system has the property of self-optimization of the error during training (Hamid *et al*. 2003). Therefore, the final weight of a particular variable was decided by the system itself, which was determined precisely by the relative impact of the variable in the dataset in relation to the actual output variable. The coefficient of determination, R^2, and the mean absolute error, *MAE,* were used to assess the performance of each developed ANN model. The performance of the network during the training and testing processes was observed for each network size until no significant improvement occurred. The optimal ANNs performance was achieved with the model having 4 neurons in the hidden layer, a 0.001 momentum factor, a log-sigmoid transfer (activation) function in the neurons of the hidden layer and in the neuron of the output layer, and 53, 50, 74, 100 and 100 epochs for the ANN models developed from Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al*. (1974), and Burland and Burbidge (1985) methods, respectively. Connection weights and biases of the best ANN models developed from Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al*. (1974), and Burland and Burbidge (1985) methods were given in Tables 4 to 8, respectively.

Table 4 Connection weights and biases of the best ANN model for Meyerhof (1965) method

Hidden neuron	Weight							Bias	
	Input neuron						Output neuron	Hidden layer	Output layer
	N_{cor}	Q	γ	D_f	B	L	Δh		
1	2.906	12.668	0.874	0.573	-33.597	1.374	0.497	-4.776	71.306
2	-133.451	29.616	-2.039	-0.512	-2.765	-1.499	0.925	-2.237	
3	1.839	-2.119	0.372	0.087	1.071	1.598	-4.042	-1.147	
4	5.864	-2.751	0.118	0.039	2.368	3.973	-72.933	5.761	

Table 5 Connection weights and biases of the best ANN model for Terzaghi and Peck (1967) method

Hidden neuron	Weight							Bias	
	Input neuron						Output neuron	Hidden layer	Output layer
	N_{cor}	Q	γ	D_f	B	L	Δh		
1	-5.941	-4.776	-0.646	0.002	7.572	19.692	-1.028	2.377	-2.217
2	-5.030	0.640	-0.096	-0.023	-0.367	-0.716	42.544	-2.725	
3	3.025	-8.258	1.355	0.315	1.757	2.154	-2.516	-1.506	
4	0.859	-4.987	0.315	-0.206	12.773	-4.158	-0.783	3.537	

Table 6 Connection weights and biases of the best ANN model for Parry (1971) method

Hidden neuron	Weight							Bias	
	Input neuron						Output neuron	Hidden layer	Output layer
	N_{cor}	Q	γ	D_f	B	L	Δh		
1	-4.390	1.170	1.521	-0.107	-0.737	-0.649	1.683	1.352	34.059
2	-3.039	-3.296	-2.207	-0.199	7.890	8.206	-1.123	3.839	
3	0.283	-3.955	1.108	0.162	0.812	0.873	-15.506	-2.996	
4	6.654	-0.834	-0.452	0.023	0.800	0.804	-36.896	3.564	

Table 7 Connection weights and biases of the best ANN model for Peck *et al*. (1974) method

Hidden neuron	Weight							Bias	
	Input neuron						Output neuron	Hidden layer	Output layer
	N_{cor}	Q	γ	D_f	B	L	Δh		
1	-0.137	-5.741	0.308	0.164	0.233	0.219	-18.206	-2.432	-1.524
2	-5.711	2.834	-0.801	0.101	-10.872	-6.517	28.379	-5.531	
3	-0.301	0.254	-0.146	0.002	-0.287	-0.290	20.426	0.769	
4	9.743	-0.343	-0.174	0.044	0.121	0.149	-14.211	2.772	

Table 8 Connection weights and biases of the best ANN model for Burland and Burbidge (1985) method

Hidden neuron	Weight							Bias	
	Input neuron						Output neuron	Hidden layer	Output layer
	N_{cor}	Q	γ	D_f	B	L	Δh		
1	-30.910	4.926	-0.228	-0.070	-15.193	-17.118	33.496	-7.359	4.239
2	3.121	0.410	0.129	0.021	0.241	0.235	-36.258	2.276	
3	-1.388	-0.854	-1.079	-0.137	3.288	3.323	-1.532	1.189	
4	-0.768	4.510	-0.729	-0.163	-0.607	-0.665	29.036	3.267	

5. Results and discussion

A comparison of Δh values calculated from five traditional methods with the Δh values predicted from the ANN models developed is depicted in Figs. 7 to 11. It can be noted from the figures that predicted Δh values are quite close to the calculated Δh values, as their R^2 values are much close to unity.

A paired-T test using the SPSS 10.0 package was also performed to test the differences between calculated and predicted Δh values. In this test, significance level was decided by taking P values into consideration as follows: $P > 0.05$ meant there was not a meaningful difference; $P < 0.05$ meant there was a meaningful difference (Tüysüz 2010). P-value was found as 0.24, 0.56**,** 0.47**,** 0.66, and 0.41 for Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al.* (1974), and Burland and Burbidge (1985), respectively, indicating that no significant difference in Δh values was observed between calculated and predicted values.

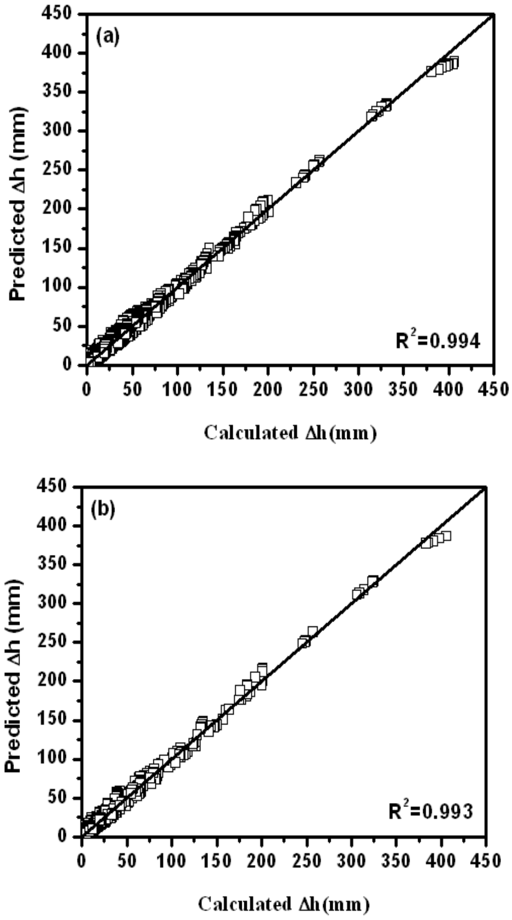


Fig. 7 Comparison of calculated Δh values from Meyerhof (1965) method with predicted Δh values from the ANN model developed for: (a) training; (b) testing; and (c) validation data sets

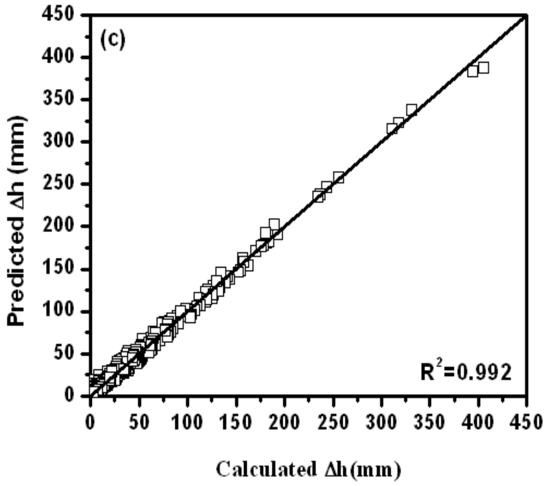


Fig. 7 Continued

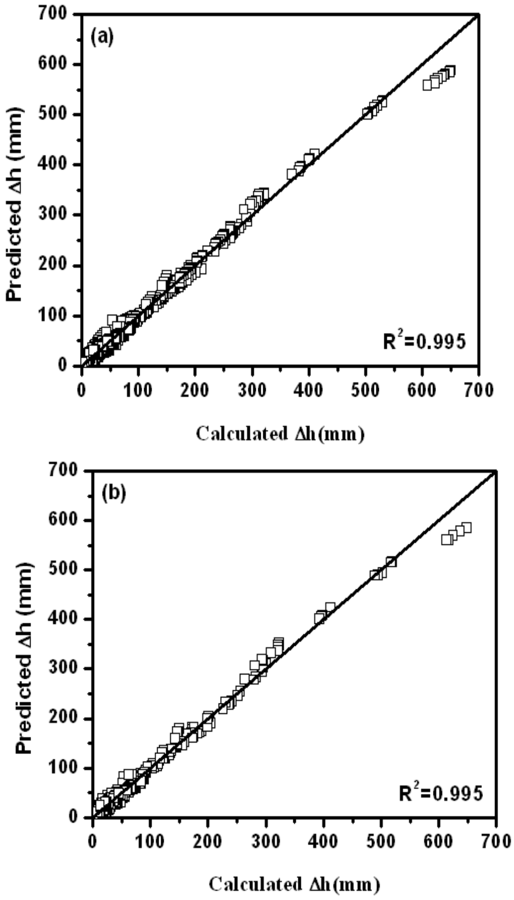


Fig. 8 Comparison of calculated Δh values from Terzaghi and Peck (1967) method with predicted Δh values from the ANN model developed for: (a) training; (b) testing; and (c) validation data sets

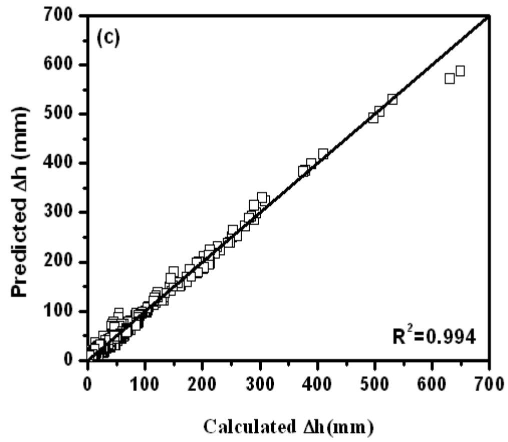
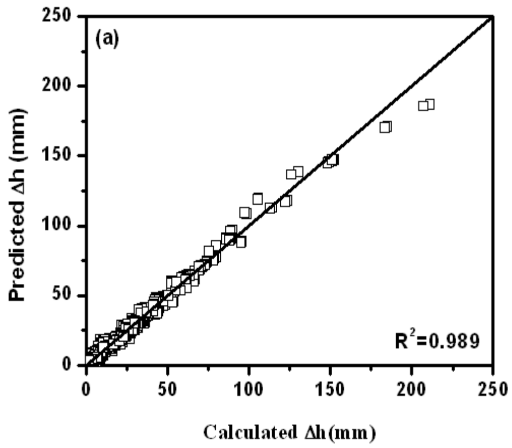


Fig. 8 Continued



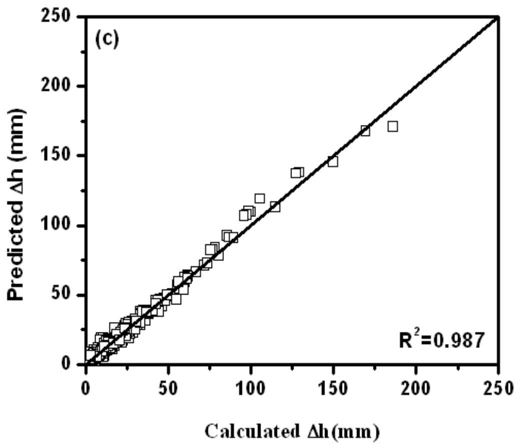


Fig. 9 Comparison of calculated Δh values from Pary (1971) method with predicted Δh values from the ANN model developed for: (a) training; (b) testing; and (c) validation data sets

Table 9 The details of the performance indices of the ANN models

Method	R^2			*MAE* (mm)			*RMSE* (mm)			*VAF* (%)		
	Training	Testing	Validation	Training	Testing	Validation	Training	Testing	Validation	Training	Testing	Validation
Meyerhof (1965)	0.994	0.993	0.992	2.60	2.88	2.91	3.66	4.14	4.03	99.38	99.35	99.21
Terzaghi and Peck (1967)	0.995	0.995	0.994	3.50	3.66	3.71	5.01	5.40	5.37	99.54	99.56	99.44
Parry (1971)	0.989	0.989	0.987	1.24	1.37	1.41	2.01	2.32	2.26	98.95	98.90	98.70
Peck *et al*. (1974)	0.986	0.986	0.985	3.42	3.66	3.79	5.90	6.47	6.27	98.65	98.62	98.46
Burland and Burbidge (1985)	0.996	0.994	0.994	0.51	0.54	0.60	0.89	0.90	1.08	99.61	99.66	99.39

In this study, variance *VAF*, represented by Eq. (7), and the root mean square error *RMSE*, represented by Eq. (8), were also calculated to check the performance of the prediction capacity of predictive models developed in the study, as employed by Erzin (2007), Erzin *et al.* (2008), Erzin *et al.* (2009), Erzin *et al.* (2010), and Erzin and Gunes (2011).

$$VAF = \left[1 - \frac{\mathrm{var}(y - \hat{y})}{\mathrm{var}(y)}\right] \times 100 \tag{7}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{8}$$

where *var* denotes the variance, y is the measured value, $\hat{y}$ is the predicted value, and N is the number of the sample. If *VAF* is 100 % and *RMSE* is 0, the model is treated as excellent.

The performance indices calculated for the ANN models developed in this study are given in Table 9. Each ANN model has exhibited higher prediction performance based on the performance indices in Table 9, which indicates the efficiency of the ANN models for estimating the settlement of pad footing on cohesionless soils.

In addition to the performance indices, a graph between the scaled percent error (SPE), given by Eq. (9), as employed by Kanibir *et al.* (2006), and cumulative frequency was also drawn in Figs. 12 to 16 for Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al.* (1974), and Burland and Burbidge (1985) methods, respectively, to show the performance of the models developed.

$$SPE = \frac{(\Delta h_p - \Delta h_c)}{((\Delta h_c)_{\max} - (\Delta h_c)_{\min})} \tag{9}$$

where Δh_p and Δh_c are the predicted and the calculated settlements; and $(\Delta h_c)_{\max}$ and $(\Delta h_c)_{\min}$ are the maximum and minimum calculated settlements, respectively. As seen from Figs. 12 to 16, about 94, 95, 95, 90, and 96 % of settlements predicted from the ANN model developed for Meyerhof (1965), Terzaghi and Peck (1967), Parry (1971), Peck *et al.* (1974), and Burland and Burbidge (1985) methods, respectively, fall into ± 2 of the SPE indicating a perfect estimate for he settlement of pad footings. From here, it can be concluded that the Δh value of pad footings for each traditional method could be predicted from the footing geometry (length, L, and width, B), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, Q, and corrected standard penetration test, N_{cor} using trained ANNs values, with acceptable accuracy, at the preliminary stage of designing the pad footing.

The settlement values predicted from the ANN models are almost the same as those obtained from the five traditional methods (see Figs. 7 to 11). Therefore, the ANN models developed can be preferred over five available methods on the basis practicality of use. Because, ANNs have the advantage that once the model is trained, it can be used as an accurate and quick tool for estimating the settlement without a need to perform any manual work such as using tables or charts as mentioned by Shahin *et al.* (2002). However, the five available methods are not easy to use as each parameter in Table 1 requires so many calculations, and use of tables or charts.

Sensivity analyses were also performed on the trained work to examine which of the input parameters has the most significant influence on settlement predictions. A simple and innovative

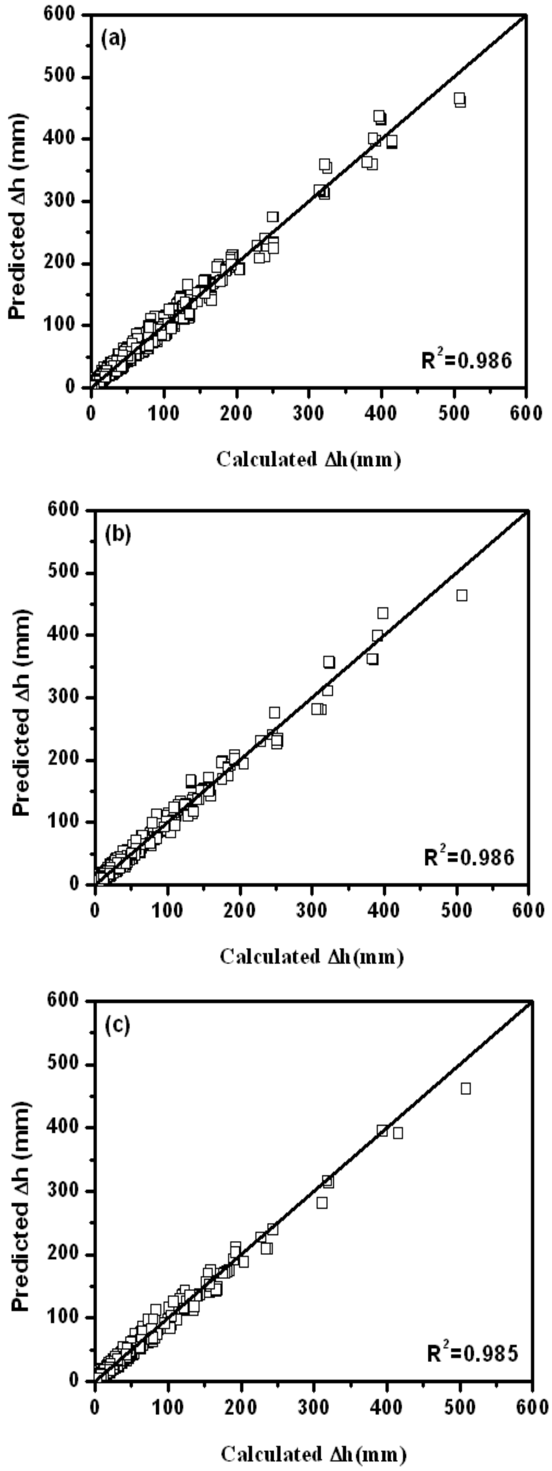


Fig. 10 Comparison of calculated Δh values from Peck *et al*. (1974) method with predicted Δh values from the ANN model developed for: (a) training; (b) testing; and (c) validation data sets

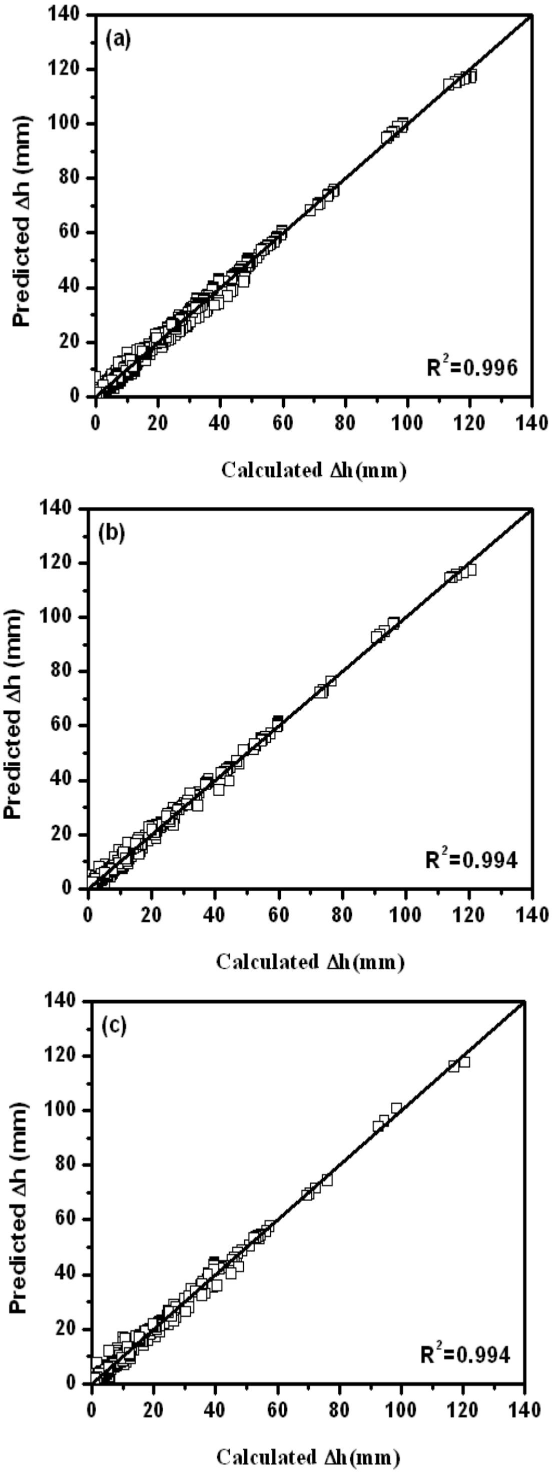


Fig. 11 Comparison of calculated Δh values from Burland and Burbidge (1985) method with predicted Δh values from the ANN model developed for; (a) training; (b) testing; and (c) validation data sets

technique proposed by Garson (1991), as employed by Shahin *et al*. (2002), was utilized to interpret the relative importance of the input parameters by examining the connection weights of the trained network. For a network with one hidden layer, the technique requires a process of partitioning the hidden output connection weights into components associated with each input node (Shahin *et al*. 2002). The ratio of the number of free parameters (e.g., connection weights)

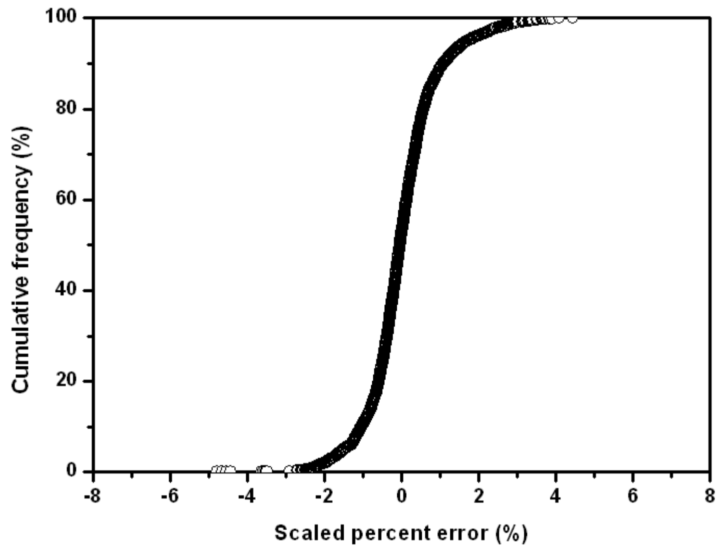


Fig. 12 Scaled percent error of the settlements predicted from the ANN model for Meyerhof (1965) method

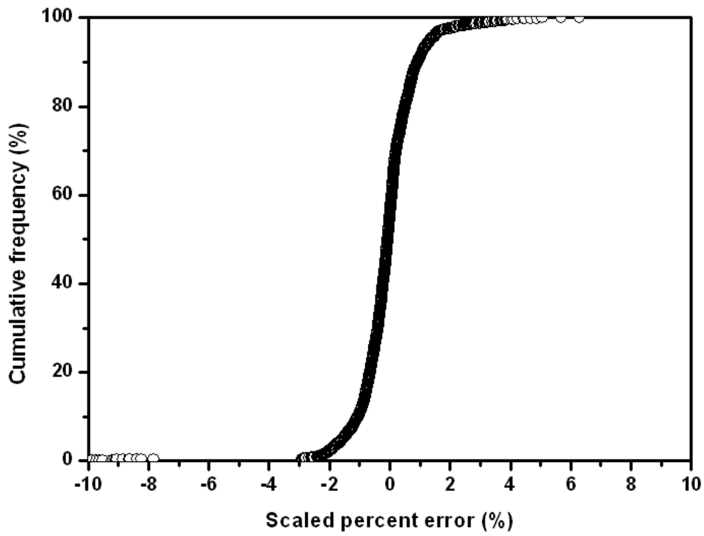


Fig. 13 Scaled percent error of the settlements predicted from the ANN model for Terzaghi and Peck (1967) method

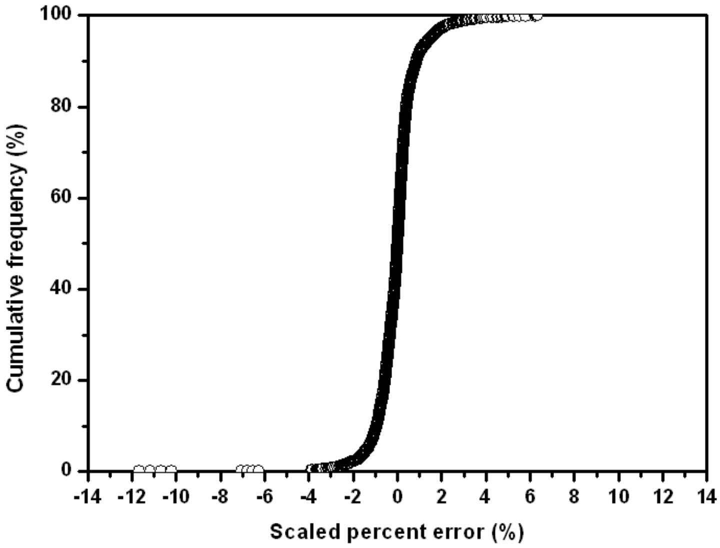


Fig. 14 Scaled percent error of the settlements predicted from the ANN model for Parry (1971) method

to the data points in the training set in any ANN model is important for interpreting of the physical meaning of the relationship found by the ANN. If this ratio is too large, the interpretation is difficult (Shahin *et al.* 2002). In this study, the ratio of the number of weights to the number of data points in the training set is approximately 1:77. Training is repeated four times with differentrandom starting weights to control the robustness of the model in relation to its ability to

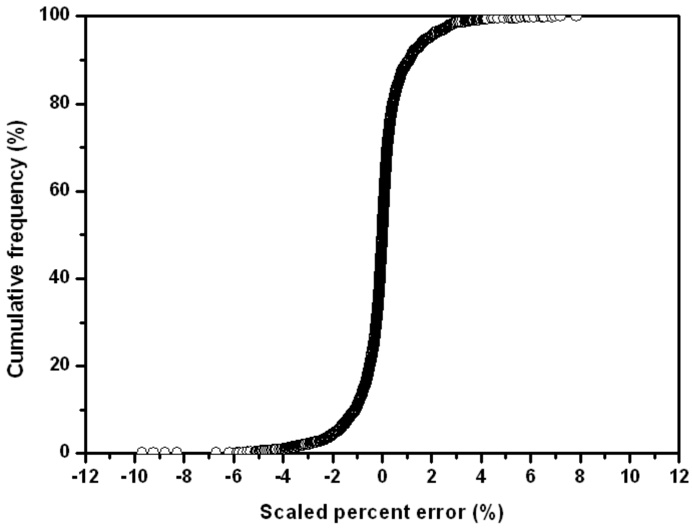


Fig. 15 Scaled percent error of the settlements predicted from the ANN model for Peck *et al.* (1974) method

Table 10 The results of the sensivity analysis

Traditional method	Trial no.	Relative importance for input variables (%)					
		N_{cor}	Q	D_f	γ	B	L
Meyerhof (1965)	1	42.62	18.49	0.95	0.30	14.94	22.71
	2	48.25	19.90	1.65	0.24	19.73	10.23
	3	55.26	15.55	1.51	0.22	15.09	12.37
	4	31.94	25.39	1.25	0.29	21.50	19.63
	Average	44.52	19.83	1.34	0.26	17.82	16.23
	Ranking	1	2	5	6	3	4
Terzaghi and Peck (1967)	1	58.16	14.46	2.14	0.49	9.63	15.12
	2	47.66	15.20	0.72	0.06	22.02	14.34
	3	43.20	16.72	0.31	0.08	24.24	15.45
	4	30.32	28.63	1.31	0.30	20.25	19.18
	Average	44.84	18.75	1.12	0.23	19.03	16.02
	Ranking	1	3	5	6	2	4
Parry (1971)	1	51.44	19.29	7.67	0.74	10.30	10.56
	2	47.65	19.65	11.13	0.68	10.39	10.50
	3	32.81	28.50	5.46	1.98	15.44	15.81
	4	44.17	27.26	7.01	1.24	13.80	6.52
	Average	44.02	23.68	7.82	1.16	12.48	10.85
	Ranking	1	2	5	6	3	4
Peck *et al*. (1974)	1	29.12	18.37	3.18	0.61	30.17	18.55
	2	36.05	15.30	25.61	0.49	11.04	11.50
	3	50.44	24.39	3.58	0.21	9.50	11.87
	4	38.82	16.72	3.08	0.48	22.51	18.39
	Average	38.61	18.69	8.86	0.45	18.31	15.08
	Ranking	1	2	5	6	3	4
Burland and Burbidge (1985)	1	43.85	11.67	1.31	0.30	20.20	22.67
	2	39.87	18.53	4.46	1.37	16.02	19.75
	3	41.13	12.01	1.03	0.23	20.99	24.61
	4	36.51	20.60	1.23	0.21	23.38	18.08
	Average	40.34	15.70	2.01	0.53	20.15	21.28
	Ranking	1	4	5	6	3	2

obtain the information about the relative importance of the physical factors affecting the settlement of pad ootings. According to the sensivity analysis (Table 10), for each traditional method, N_{cor} is found to be the most important parameter while γ is found to be the least important parameter. In addition to that, the secondly important parameter was Q for Meyerhof (1965), Parry (1971), and Peck *et al*. (1974) methods, L for Burland and Burbidge (1985) and B for Terzaghi and Peck (1967).

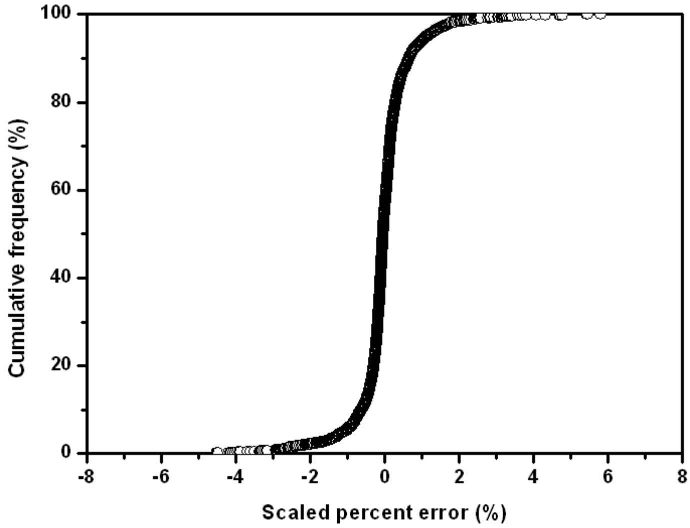


Fig. 16 Scaled percent error of the settlements predicted from the ANN model for Burland and Burbidge (1985) method

6. Conclusions

In this study, attempts have been made to develop artificial neural network (ANN) model that can be employed for predicting the settlement, Δh, of pad footings on cohesionless soils, without a need to perform any manual work such as using tables or charts. With this purpose in mind, a computer program was developed in the Matlab programming environment to calculate the Δh value of pad footings from five traditional settlement prediction methods. The footing geometry (length, L, and width, B), the footing embedment depth, D_f, the bulk unit weight, γ, of the cohesionless soil, the footing applied pressure, Q, and corrected standard penetration test, N_{cor}, varied during the settlement analyses and the Δh value of each pad footing was calculated for each method by using the written programme. Then, an ANN model was developed for each traditional method to predict the Δh value of pad footings by using the results of the settlement analyses. The Δh values predicted from the ANN model were compared with those calculated from the traditional method for each method to check the performance of the prediction capacity of the models developed in the study. It is found that the Δh values predicted from the ANN model are quite close to the calculated Δh values for each method.

In order to examine the prediction performance of the ANN models developed, several performance indices such as R^2, *VAF*, *MAE*, *RMSE*, and *SPE* were computed. Each ANN model has shown high prediction performance based on the calculated performance indices, which demonstrates the utility and efficiency of the ANN models for estimating the settlement of pad footing on cohesionless soils. Therefore, the ANN models developed in this study can be used as an accurate and quick tool at the preliminary designing stage of pad footings on cohesionless soils without a need to perform any manual work such as using tables or charts.

Sensivity analyses were also carried out on the trained work to identify which of the input parameters has the most significant influence on settlement predictions. It is found that for each traditional method, N_{cor} is found to be the most important parameter while γ is found to be the least important parameter.

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