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APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN GEOTECHNICAL ENGINEERING

Nabeel S. Juwaied
College of Engineering, Department of Civil Engineering, Al-Nahrain University, Baghdad, Iraq
E-Mail: nabeeljuwaied@yahoo.com

ABSTRACT

The use of artificial intelligence (AI) techniques to deal with complex geotechnical problems has recently escalated. Which may be the result of lack of efficiency of traditional methods, or the promising potential of these techniques to represent such complexity. Artificial intelligence has been applied in most areas of geotechnical engineering. In this research, these applications were extensively reviewed and discussed. Where they showed great success in most of them.

Keywords: artificial intelligence artificial, neural networks, bearing capacity of piles, settlement of foundation, soil liquefaction.

1. INTRODUCTION

Civil engineering deals with enormous variety of materials, most of civil engineering materials, such as concrete, steel, and timber, which show more homogeneity and isotropy, some of these we can considered it almost as manufactured product, like reinforced concrete, with high possibility control of quality during the production. Some other important components are completely natural, like soil.

Geotechnical engineering deals with materials (e.g., soil and rock). the engineering properties of soil and rock show varied and uncertain behavior due to the complex and imprecise physical processes associated with the formation of these materials (Jaksa ,1995). Many complexity and uncertainty related with geotechnical engineering materials and it properties. Some sources of uncertainty are incoherent soil composition, errors in soil boring, sampling, in-situ and laboratory testing, and characterization of the shear strength and stiffness of soils, and loading effects, time effects, construction effects, human error. As an example difficulty in obtaining undisturbed samples as in sand and gravel, cause uncertainty of laboratory testing results, and the same clayey soil often exhibits uncertain behavior from one location to another.

The mathematical model is a form created in science. The fundamental principles of physics and mechanics have been used to create this model, and used to predict, simulate, and analyze system behavior. The mathematical model will be appropriate when known the basic condition of a system, the measured inaccuracy and uncertainty did not decrease the accuracy of the model (Rahman and Mulla, 2005). Because, the complexity in geotechnical problems, its exact solution is the probability (Djajaputra, 1997; Griffith *et al.*, 2002).

Traditional forms of engineering modelling approaches are very simplified to deal with the such complexities. Some promise is appearing in alternative approach “Artificial intelligence (AI)”, which has showed succeeded in the field of geotechnical engineering.

Artificial intelligence (AI) has been shown high predictive ability comparing to traditional methods and as a result of that, it became widely usable in modeling the complex behavior of most geotechnical engineering materials. Using AI has main advantage of over regression in process modeling, which is capacity in dealing with multiple outputs or responses while each regression model is able to deal with only one response (Park, 2011). Additional to that (Park,2011) referred to another major advantage for developing NN process models is that they do not depend on simplified assumptions such as linear behavior or production heuristics make it very suitable to represent materials with many deferent properties as soil. Neural networks have a number of important properties for modeling a complex mechanical behavior: good generalization capability, universal function approximation capability, resistance to noisy or missing data, and accommodation of multiple nonlinear variables for unknown interactions.

On can notes that starting from 90s, there is increasingly in employed AI as an effective tool in geotechnical engineering. AI techniques are artificial neural networks (ANNs), genetic programming (GP), evolutionary polynomial regression (EPR), support vector machines, M5 model trees, and K-nearest neighbors (Elshorbagy *et al.*, 2010), among AI techniques, artificial neural networks (ANNs) most successful applied in geotechnical engineering including.

2. APPLICATION OF AI IN GEOTECHNICS

2.1 Site characterisation

The main objective of site characterization is the prediction of *in situ* soil properties at any half-space point at a site based on limited tests. Site characterization is an area concerned with the analysis and interpretation of geotechnical site investigation data. A multi-layer feed forward neural network is used by (Zhou and Wu, 1994) to capture the spatial distribution of the granite rock head by training the network with sample data from seismic refraction surveys on over 11 km of traverse lines with shot-point spacing of 50 and 25 meters for geophones placed at 10 and 5 meters, respectively. The neural network model requires information on the coordinates (x,y) and surface elevation of a survey point in the input to characterize the spatial distribution of rock head elevations characterize the spatial distribution of rock head elevations. The trained network was tested to estimate the rock head elevations for all locations within the area of investigation by producing a corresponding contour map. Results from the neural network model compare very well with similar contour maps generated using kriging techniques. The main advantage of this neural network based approach is its ability in establishing patterns or relationships through training directly on the data without building any complicated mathematical models and making assumptions on spatial variations.

Najjar and Basheer (1996a); Basheer *et al*. (1996) discussed application related to ground water characterization by used neural networks to map the variation of permeability for purposes of identifying boundaries of landfill to be constructed on a real site. The neural network, as a simple technique, was found to be able to logically predict the variation. The sensitivity of the produced permeability maps to both the quality and number of observations was also studied to investigate the accuracy of the proposed mapping methodology. Concluded that, the use of neural networks as a mapping tool can help identify the regions within a site where additional subsoil exploration is warranted.

Rizzo and Dougherty (1996) applied and tested a new pattern method on a variety of site characterization problems, called it "SCANN" (Site characterization using Artificial Neural Networks), is based on the application of artificial neural networks. Applications include developing maps of discrete spatially-distributed fields (e.g. log-hydraulic conductivity fields) given estimates of hydraulic conductivity from pumping tests and classifying soil lithology given soil sample descriptions from driller well logs. Unlike the kriging methods, SCANN is data-driven and requires no estimation of a covariance function. It uses a feed-forward counter propagation training approach to determine a "best estimate" or map of a discrete spatially-distributed field.

Gangopadhyay *et al* (1999) developed a multilayer perceptron using the back-propagation algorithm for characterizing the subsurface and geographic information system (GIS) the integrated approach of ANN and GIS, is shown to be a powerful tool for characterizing complex aquifer geometry, and for calculating aquifer parameters for ground-water flow modeling.

Besaw *et al* (2006) present a subsurface characterization methodology that integrates multiple types of data using a modified counter propagation artificial neural network (ANN) to provide parameter estimates and define groundwater contamination at a leaking landfill. The results of this research illustrate the feasibility of combining principal component analysis (used to reduce data dimensionality) with the counter propagation ANN and traditional geostatistical methods (kriging) to estimate subsurface contamination. This research demonstrates the potential for applying this ANN estimation technique (as an alternative to kriging) to delineate the leachate contaminated groundwater and evaluate water quality associated with subsurface contamination at a full scale site. These results suggest the counter propagation ANN is a promising parameter estimation method when integrating multiple data types to enhance prediction accuracy and reduce uncertainty.

Samui (2012) based on large amount of Standard Penetration Test, used the Support Vector Machine (SVM), to develop a three dimensional site characterization model. Also a sensitivity analysis of SVM parameters (σ, C, and ε) has been presented. The results obtainable in this paper clearly highlight that the SVM is a strong tool for site characterization.

Gomes *et al*. (2016). discussed the prediction of spatial patterns in the depth to bedrock (DTB) using high-resolution topographic data, numerical modeling, and Bayesian analysis has been introduced the different building blocks of a DTB model to predict the vertical extent of the weathered rock underling soil-mantled hillslopes from a high-resolution topographic map of the soil surface. Two case studies with synthetic and real-world regolith depth data were used to illustrate the effectiveness and applicability DTB model and methodology. The results demonstrate that the proposed DTB model with lumped parameters mimics reasonably well the observed regolith depth data with root mean square error (RMSE).

2.2 Soil properties and behaviour

There is an increasing in employment of ANNs in modelling soil properties and its behavior. Poor learning resulting from overtraining the network was studied using artificially generated triaxial data. (Penumadu *et al*., 1994), provide modelling rate-dependent behavior of clay soils. Neural network methods have been used for estimating the permeability of clay liners by Gribb and Gribb (1994); Agrawal *et al.*, 1994); and Najjar and Basheer, 1996b).

Goh (1995a; 1995c). provide a study demonstrates the feasibility of using neural networks for capturing nonlinear interactions between various parameters in complex civil engineering systems. A simple back-propagation neural network was used to model two problems involving engineering correlations between various soil parameters were used to model the correlation between the relative density and the cone resistance from cone penetration test (CPT), for both normally consolidated and over-consolidated sands. Based on calibration chamber tests, laboratory data, were used to successfully train and test the neural network model. By used as inputs the relative density and the mean effective stress of soils and the CPT cone resistance as a single output. The model gave 0.97 and 0.91 for the training and testing data, respectively, which it high value of correlation coefficients, meaning that the neural network was successful in modelling the non-linear relationship between the CPT cone resistance and the other parameters.

Ellis *et al*. (1996), used (ANNs) for modeling the stress-strain relationship of sands with varying grain size distribution and stress history. A series of undrained triaxial compression tests for eight different sands was performed under controlled conditions to develop the database and was used for neural network training and testing. An attempt has been made to implement artificial neural networks (ANNs) for modeling the stress-strain relationship of sands with varying grain size distribution and stress history. A series of undrained triaxial compression tests for eight different sands was performed under controlled conditions to develop the database and was used for neural network training and testing. The investigation confirmed that a sequential ANN with feedback is more effective than a conventional ANN without feedback, to simulate the soil stress-strain relationship. The study shows that there is potential to develop a general ANN model that accounts for particle size distribution and stress history effects. Also demonstrated the ability of neural networks to simulate unload-reload loops of the soil stress-strain characteristics. This study showed that artificial-neural-network-based soil models can be developed by proper training and learning algorithms based on a comprehensive data set, and that useful inferences can be made from such models.

Cal (1995) based on three factors (plastic index, liquid limit and clay content) introduced a model to a quantitative soil classification by using a neural network.

Romero and Pamukcu (1996) used (ANN) successfully to characterize and estimate the shear modulus of granular materials.

Najjar *et al.* (1996) a huge data base representing 413 soils retrieved from 45 different projects was used to develop prediction models. Neural network-based models and a statistical model were developed. Showed that neural models provide significant improvements in prediction accuracy over statistical models.

Penumadu and Jean-Lou (1997) provided a model to simulate the behavior of sand and clay soils by using (ANN). Ghaboussi and Sidarta (1997) introduced nested adaptive neural networks; a new type of neural network developed by Ghaboussi, and applied this neural network in modeling of the constitutive behavior of geomaterials. Nested adaptive neural networks take advantage of the nested structure of the material test data, and reflect it in the architecture of the neural network. This new neural network is applied in modeling of the drained and undrained behavior of sand in triaxial tests.Also, Zhu *et al.* (1998a; 1998b) provide a modelling the shearing behavior of a fine-grained residual soil, dune sand and Hawaiian volcanic soil used ANNs. Then Penumadu and Zhao (1999) used ANNs to model volume change and the stress-strain behavior of sand and gravel under drained triaxial compression test conditions.

Ikizler *et al* (2009) developed prediction model of transmitted lateral swelling pressure, and vertical swelling pressures on a retaining structure using artificial neural network (ANN) approach. In the first stage of this study, the lateral and vertical swelling pressures were measured with different thicknesses of expanded polystyrene (EPS) geofoam placed between one of the vertical walls of the steel testing box and the expansive soil. Then, artificial neural network was trained using these pressures for prediction transmitted lateral swelling pressure, and vertical swelling pressures on a retaining structure. Results obtained from this study showed that neural network-based prediction models could satisfactorily be used in obtaining the swelling pressures of the expansive soils. After that, Ikizler *et al* (2012) provided, a new estimation model to predict the pressures is developed using experimental data. The data were collected in the laboratory using a newly developed device and experimental setup also. In the experimental setup, a rigid steel box was designed to measure transmitted swelling pressures in lateral and vertical directions. In the estimation model, approaches of artificial neural network (ANN) and adaptive neuro-fuzzy inference systems (ANFIS) are employed. In the first stage of the study, the lateral and vertical swelling pressures were measured with different thicknesses of expanded polystyrene geofoam placed between one of the vertical walls of the steel box and the expansive soil in the laboratory. Then, ANN and ANFIS approaches were trained using these results of the tests measured in the laboratory as input for the prediction of transmitted lateral and vertical swelling pressures. Results obtained showed that ANN based prediction and ANFIS approaches could satisfactorily be used to estimate the transmitted lateral and vertical swelling pressures of expansive soils.

Tizpa *et al* (2014). presented artificial neural network prediction models which relate compaction characteristics, permeability, and soil shear strength to soil index properties. A database including a total number of 580 data sets was compiled. The database contains the results of grain size distribution, Atterberg limits, compaction, permeability measured at different levels of compaction degree (90-100 %) and consolidated–drained triaxial compression tests. Comparison between the results of the developed models and experimental data indicated that predictions are within a confidence interval of 95 %. According to the performed sensitivity analysis, Atterbeg limits and the soil fine content (silt+clay) are the most important variables in predicting the maximum dry density and optimum moisture content. Another aspect that is coherent from the sensitivity analysis is the considerable importance of the compaction degree in the prediction of the permeability coefficient. However, it can be seen that effective friction angle of shearing is highly dependent on the bulk density of soil

2.3 Pile capacity

Evaluation pile bearing capacity usually performed in situ by static load test (SLT). But, procedure of SLT is always costly and time-consuming. Recently high strain dynamic pile testing (HSDPT) which is provided by pile driving analyzer (PDA) is used for prediction pile axial bearing capacity. The prediction pile capacity is always a problematic case, many approximate method has been used, but always there is need to a method has the ability in finding complex nonlinear relationships between different parameters. Therefore, many researchers used neural networks in pile capacity.

Goh (1994a; 1995b), neural network was applied to predict the friction capacity of piles in clays. Goh used empirical data of actual field case records to training the neural network and to evaluate friction capacity fs on a side surface of timber and steel pipe driven piles. After piles were driven in soft and very soft clays. The data were collected. The model input data were: embedded pile length (4.7-96.0) m; pile diameter (13.5-76.7) cm; vertical component of mean effective stress σ'v (19-718 KPa); and undrained shear strength su (9-335 kPa). The output was skin friction capacity from compression tests of piles fs (8.0-192.1) KPa. Prediction results of friction capacity fs were compared with the results obtained by the conventional prediction methods of (Semple and Rigden, 1986) and the β method (Burland 1973). The results for the neural network models with three hidden neurons are summarized in Table1. NN model had the highest coefficient of correlation and lowest error rate for the training and testing data.

Table-1. Summary of correlation coefficients and error rate for friction pile capacity (Goh 1995b).

Method	Coefficient of correlation		Error rate (kPa)	
	Training	Testing	Training	Testing
NN	0.985	0.956	1.016	1.194
Semple and Rigden (1986)	0.976	0.885	1.318	1.894
β method	0.731	0.704	4.824	3.096

The neural network predictions from the training and testing sets for NNs model are shown in Figure-1. The results indicate that the neural network was successful in modelling the non-linear relationship between fs, and the other parameters. Comparisons were also made between the measured fs, values and the values predicted using the β method (Burland, 1973) and the method of (Semple & Rigden, 1986), as plotted in Figure-2 and Figure-3 the neural network resulting Figure-1 show less scatter in the data points.

The back propagation approach was successfully applied to evaluate the friction capacity of driven piles in clay from actual field records. Also the study pointed out that the main shortcoming of the neural network methodology is its inability at present to trace and explain the step-by-step logic it uses to arrive at the outputs from the inputs provided.

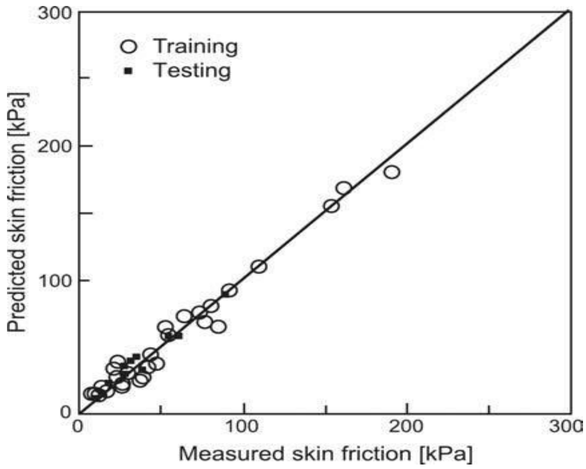

Figure-1. Skin friction fs - comparison of values predicted by NNs with standards from measurements.

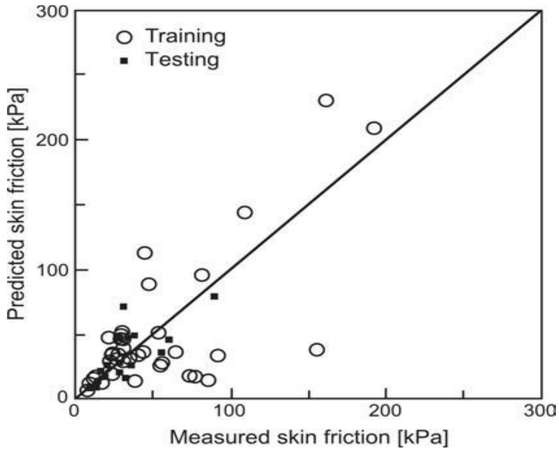

Figure-2. Skin friction fs - comparison of values calculated according to Semple and Ridgen's method with standards from measurements.

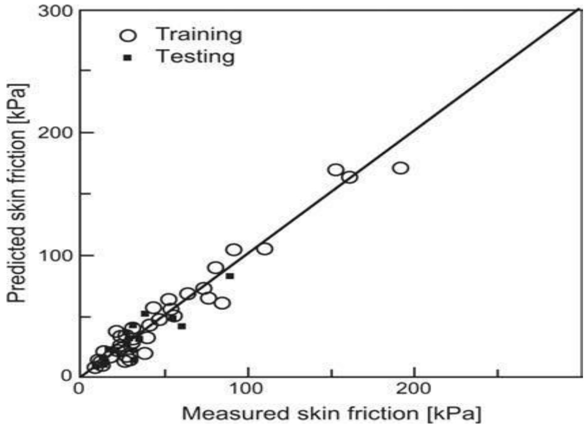

Figure-3. Skin friction fs - comparison of values calculated according to method with standards from measurements.

Then (Goh, 1995a; 1996b), estimated the ultimate load capacity of driven piles in cohesionless soils by using an ANNs and data were drawn from actual case records compiled by(Flaate, 1964) for timber, precast concrete and steel piles in cohesionless soils. The inputs to the ANN model were the hammer weight, the hammer drop, hammer type, the pile length, the pile weight, the pile modulus of elasticity the pile cross sectional area, and the pile set. The pile load capacity Qu was the output neuron. High coefficients of correlations for the training and testing data were obtained; Goh summarized it in a Table-2. The results from the testing phase suggest that although the model was not explicitly trained for these data, the neural network was capable of generalization and generally gave reasonable predictions. The results indicate that the neural network was successful in modeling the nonlinear relationship between QU and the other parameters.

Depending on the connection weights, the hammer weight, the pile set, and the hammer type, are that the more important input factors. As showed in Table-2 the study used coefficients of correlation of predicted versus measured results for compared NNs results with that obtained by the following common relationships: The Engineering News formula (Wellington 1892), the Hiley formula (Hiley 1922) and the Janbu formula (Janbu 1953). They indicate that the neural network predictions are more reliable than the conventional pile driving formulae. Also the study, indicated important point, during training, unrelated input variables are assigned low connection weights. These variables can then be omitted from the model.

Table-2. Summary of regression analysis results of pile capacity prediction (Goh 1995a).

Method	Coefficient of correlation	
	Training data	**Testing data**
Neural network	0.96	0.97
Engineering News (EN)	0.69	0.61
Hiley	0.48	0.76
Janbu	0.82	0.89

Chan *et al.* (1995), introduced a neural network model were the inputs including the pile driving energy, the elastic compression of the soil and pile, and the pile set, which it the same parameters recorded in the simplified Hiley formula (Broms and Lim 1988), as an alternative to pile driving formulae. The pile capacity was the model output. The study estimated the value of pile capacity that was used in the training process by using a commercial computer code called CAPWAP (Rausche *et al.*, 1972) or the CASE method (Goble *et al.*, 1975).

Lee and Lee (1996), utilized error back propagation neural networks to predict the ultimate bearing capacity of piles. For the verification of applicability of neural networks, results of model pile load tests performed by the authors were simulated, were the model inputs, the penetration depth ratio (i.e. Penetration depth of pile/pile diameter), the mean normal stress of the calibration chamber and the number of blows. The model output was the ultimate bearing capacity. In addition, the results of in situ pile load tests obtained from a literature survey were also used. Five input variables were used representing the penetration depth ratio, the average standard penetration number along the pile shaft, the average standard penetration number near the pile tip, pile set and hammer energy. The results showed that the maximum error of prediction did not exceed 25%, except for some bias data. Then based on the average standard penetration, the results were compared with Meyerhof's equation (Meyerhof 1976). The results showed that the neural networks predicted values corresponding the measured values much better than those obtained from Meyerhof's equation. These limited results indicated the feasibility of utilizing neural networks for pile capacity prediction problems.

Teh *et al.* (1997), proposed a back-propagation neural network model for estimating static pile capacity from dynamic stress wave data. The training and testing of the network were based on a database of 37 precast reinforced concrete (RC) piles from 21 different sites. The CAPWAP (Rausche *et al.* 1972) -predicted soil parameters were used as the desired output in training. Three different network models were used to study the ability of the neural network to predict the desired output to increasing degree of detail. The study showed that the neural network model predicted the total capacity reasonably well. The neural-network-predicted soil resistance along the pile was also in general agreement with the CAPWAP solution. The capability of the network to generalize from limited training examples was verified by its performance against dynamic test data obtained from non-RC piles.

Abu-Kiefa (1998), the present study introduces three general regression neural network models. The first model, GRNNM1, was developed to estimate the total pile capacity. The second model, GRNNM2, was introduced to estimate the tip pile capacity. The last model, GRNNM3, was utilized to estimate the shaft pile capacity. Data from 59 good-quality pile load tests in granular soils were utilized to construct the networks. Pile capacity predictions were made using GRNNMI as well as four other empirical techniques, and they were also compared with actual measurements. These other methods are those proposed by (Meyerhof, 1976): (Coyle and Castello, 1981), the American Petroleum Institute (RP2A 1984), and It may be concluded that the GRNNMI is applicable for all different conditions of driven piles in cohesionless soils. (Randolph, 1985). Figure-4 shows the relationship between measured and predicted values for each of the five methods. This figure indicates that the new method provides the best prediction for total pile capacity. It is clear that GRNNMI is also applicable for all conditions of driven piles in granular soils, in contrast to the other procedures, which are limited to certain conditions and usually produce inconsistent results.

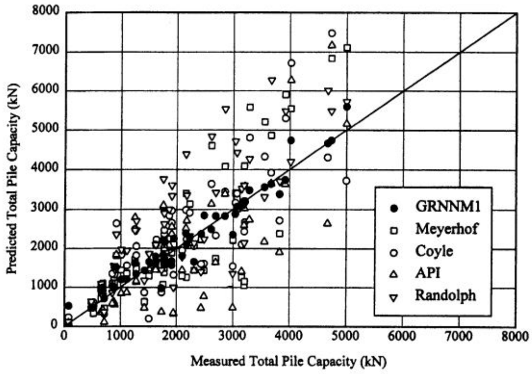

Figure-4. Comparison of predicted and measured total pile capacity (Abu-Kiefa 1998).

A comparison between the measured tip pile capacities and the predicted values from GRNNM2 for both the training and the testing sets was showed very high coefficients of correlation. The tip pile capacity predictions using both the previous empirical procedures and GRNNM2 were compared with actual measurements. Figure-5 showed the relationship between measured and predicted values for each of the five methods. Clearly, the GRNNM2 prediction shown in Figure-5 provided the best prediction of tip pile capacity. The proposed method is superior to the empirical ones when compared with actual measurements.

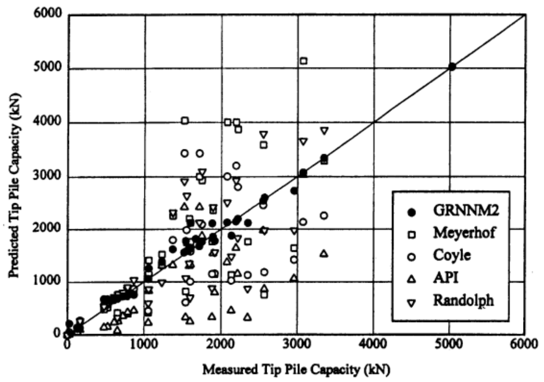

Figure-5. Comparison of predicted and measured tip pile capacity (Abu-Kiefa 1998).

A comparison between the measured shaft pile capacities and the predicted ones from GRNNM3 for both the training and the testing sets was showed very high coefficients of correlation were obtained. The shaft pile capacity predictions using the previous empirical procedures as well as GRNNM3 were also compared with actual measurements. The relationship between measured and predicted values for each of the five methods is shown in Figure-6. From this figure, it is most evident that GRNNM3 also provides the best prediction for shaft pile capacity.

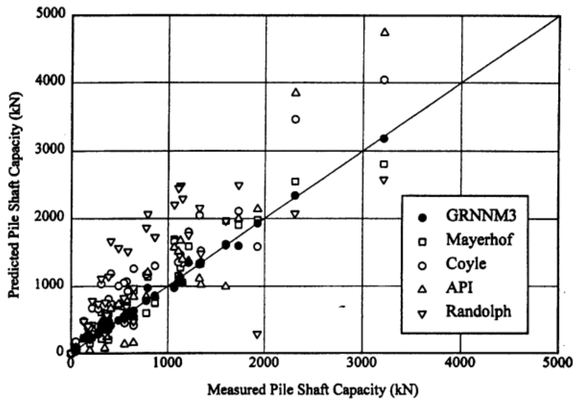

Figure-6. Comparison of predicted and measured shaft pile capacity (Abu-Kiefa 1998).

Goh *et al* (2005) used a Bayesian neural network algorithm to model the relationship between the soil undrained shear strength, the effective overburden stress, and the undrained side resistance alpha factor for drilled shafts. The study integrated the Bayesian framework into the backpropagation algorithm to enhances the neural network prediction capabilities, also provides assessment of confidence (error bars) associated with the network predictions. Both the load test results and the parametric studies using the trained neural network suggest that the effective overburden stress sv8m directly or indirectly has an influence on the a CIUC value for drilled shafts. The developed neural network model provided good estimates of the undrained side resistance adhesion factor. Furthermore, one distinct benefit of this neural network model is the computation of the error bars on the predictions of the adhesion factor. These error bars will aid in giving confidence to the predicted values and the interpretation of the results.

Nawari *et al.* (1999), introduced Neural network paradigms for the design of piles subjected to axial and lateral loads. N-SPT value and pile dimension were the inputs of the network for training and testing phases. During the training phase, the measured axial pile capacities were compared with the capacities obtained by BPNN. The artificial neural network based design approach consists of feed forward back propagation Neural Network, and Generalized Regression Neural Network. According to the simulation results, the neural network approach is feasible and was found to be more accurate than the commonly used techniques for the design of pile foundations.

The GRNN model has the advantage that it is unnecessary to define the number of hidden layers or the number of neurons per layer in advance. Moreover, the GRNN provides an adequate approximation of the full-scale pile test results. Based on the results from this investigation, it appeared that the proposed neural network models furnish a pragmatic and a reliable alternative for the current analysis and design techniques of axial pile capacity and laterally loaded piles.

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Park and Cho (2010). (165) data from dynamic piles load test at various sites were selected to develop an ANN model to predict the resistance of the driven pile in dynamic load test. The results showed that the ANN model served as a reliable and simple predictive tool to predict the resistance of the driven pile with correlation coefficient values close to 0.9.

Shahin (2010), utilized artificial neural networks (ANNs), to developed two ANN models (one for driven piles and the other for drilled shafts) were developed with the aid of the software package NEUFRAME Version 4.0 (Neusciences 2000). The data used to calibrate and validate the ANN models are obtained from the literature and include a series of 80 in situ driven pile load tests reported by (Eslami, 1996) and 94 in situ drilled shaft load tests reported by (Alsamman, 1995), as well as CPT results. Then the author compared predictions from the ANN models with those obtained from the most commonly used available CPT-based methods:

- Eslami and Fellenius (1997)
- LCPC (Bustamante and Gianeselli 1982)
- European method (de Ruiter and Beringen 1979).

and statistical analyses were carried out to rank and evaluate the performance of the ANN models and CPT methods.

Usually the produced equations of the developed ANN models, difficult to use, so the author, translated it into simple design equations suitable for hand calculations. The results indicate that the ANN models were capable of accurately predicting the ultimate capacity of pile foundations with high coefficients of correlation, r. For driven piles, the ANN model had a coefficient of correlation (r) of 0.96 and 0.85 in the calibration and validation sets, respectively, whereas the ANN drilled shafts model had an r of 0.97 in both the calibration and validation sets. The sensitivity analyses carried out on both the driven piles and drilled shafts ANN models indicated that predictions from the ANN models compare well with what one would expect based on available geotechnical knowledge and experimental results.

Wardani *et al*. (2013), applied NN model for prediction of ultimate bearing capacity of single pile foundation, was named NN_Qult model. The results of analysis model were then compared with (Meyerhof, 1976) and (Briaud ,1985) formulas. At the stage of modeling, data from full-scale pile load test and SPT were used. The selected input variables are: d (pile diameter), L (length of the pile embedded), the N60 (shaft) value, and the N60 (tip) value. The study generated design Charts that are expected to predict the ultimate bearing capacity of a single pile foundation. The design chart is used as a tool to calculate the ultimate bearing capacity of a single pile in sand soil. The results showed that neural networks can be used for prediction of ultimate bearing capacity of single pile foundation. This is particularly due to the sensitivity analysis results indicated the suitability of artificial neural network model with existing theories. The results of the model have the highest performance among the other methods, even though the difference is not too big.

Lee *et al* (2014), adopted artificial neural networks (ANN), to generate the training samples for training ANN, finite element (FE) analysis was performed 50 times for 50 different design cases. The trained ANN was verified with another FE analysis case and then used as a structural analyzer. The multilayer neural network (MBPNN) with two hidden layers was used for ANN. The framework of MBPNN was defined as the input with the lateral forces on the jetty structure and the type of piles and the output with the stress ratio of the piles. Through the trained MBPNN, the stress ratios of jetty piles were obtained under different loading conditions which were not included in the training samples. The feasibility of the MBPNN was verified by comparing the results from FE model and the MBPNN. The results from the MBPNN are very close to the FE analysis results. The RMSE is also very small regardless of the pile patterns. For the highly complex jetty pile patterns the results from the MBPNN show very good agreement with those from FE analysis. With the more training samples and the expansion of input parameters for jetty structure design, the MBPNN showed possibility to replace the repetitive and time-consuming FE analysis. Also the study referred to that only 50 cases had been modeled for this study, the merit of MBPNN would be clearer as the number of cases increases.

Maizir *et al*. (2015), development ANN model for prediction of axial capacity of a driven pile based on Pile Driving Analyzer (PDA) test data. As many as 300 sets of high quality test data from dynamic load test performed. Input considered in the modeling are pile characteristics (diameter, length as well as compression and tension capacity), pile set, and hammer characteristics (ram weight, drop height, and energy transferred). An ANN model (named: ANN-HM) was developed using a computerized intelligent system for predicting the total pile capacity as well as shaft resistance and end bearing capacity for various pile and hammer characteristics. The results show that the ANN-HM serves as a reliable prediction tool to predict the resistance of the driven pile with coefficient of correlation (R) values close to 0.9 and mean squared error (MSE) less than 1% after 15,000 number of iteration process.

Mazaher and Berneti, (2016), applied MLP neural network for prediction of load carrying capacity of open ended metal piles pounded in sandy soils. Four parameters of pile length, its diameter, soil elastic modulus and soil internal friction angle are used as input and pile load carrying capacity is applied as output.

Obtained results revealed that neural network with minimum error, high speed and learning capacity, has very high efficiency in predicting load carrying capacity of metal piles. Also based on performed sensitivity analysis on the best obtained network, all parameters have an increasing effect on load carrying capacity and according to sensitivity values and their distances from base line, it is concluded that soil internal friction angle, soil elastic modulus, pile diameter and pile length respectively have maximum effect on load carrying capacity of piles.

2.4 Settlement of foundations

Two criteria that govern foundation design, bearing capacity and settlement; often settlement governing. It is very complex to estimating the settlement of foundations, uncertain and not yet entirely understood. So, many researchers encouraged by the previews succeed of ANN techniques in complex problems to apply it in settlement prediction.

Goh (1994a), proposed a ANN model for the prediction of settlement of a vertically loaded pile foundation in a homogeneous soil stratum. The inputs were the ratio of the elastic modulus of the pile to the shear modulus of the soil, pile length, pile load, shear modulus of the soil, Poisson's ratio of the soil and radius of the pile. The pile settlement was the output. The target output used for training the ANN model was obtained by means of finite element and integral equation analyses by (Randolph and Wroth, 1978). The results indicated the successfully of the ANN model to predict the settlement of pile foundations.

Sivakugan *et al.* (1998) attempted use neural network for predicting settlements of shallow foundations on granular soils. Five inputs were used to train the neural network: average blow count from the standard penetration test, net applied pressure, width of foundation, shape of foundation and depth of foundation. The output was the settlement of the foundation. Settlement of the foundation was the output. 79 settlement records with necessary foundation and soil data were collected from the literature. Out of the 79 records, 69 were used to train the neural network and the remaining ten were used to test the network. The predictions are compared with those from two traditional methods, (Terzaghi and Peck, 1967) and (Schmertmann, 1970). The results showed that the traditional method of Terzaghi and Peck and Schmertmann's method overestimate the settlements by about 2.18 times and 3.39 times respectively; the neural network model predictions were very good.

Arnold (1999) used the same features of NN model prepared by (Sivakugan *et al.*, 1998) with a larger number of data cases. His neural network model contained 18 hidden layer nodes with correlation coefficients equal to 0.954, 0.955 and 0.944 for the training, testing and validation sets, respectively. (Shahin *et al.,* 2004a) mentioned that 18 hidden layer nodes are considered to be large for a network with 5 input variables, which may affect the generalization ability of the model. Also mentioned that the ANN models developed above for settlement prediction of shallow foundations on cohesionless soils have been built on either a limited number of data cases (e.g. Sivakugan *et al.* 1998) or have suffered from the lack of a comprehensive procedure for testing their robustness and generalization ability (e.g. Arnold 1999).

Shahin *et al*. (2000) attempted to carried out similar work for predicting the settlement of shallow foundations on cohesionless soils. Using a large database of actual measured settlements. In his work, 272 data records were used for modelling. The input variables considered to have the weightiest influence on settlement prediction were, the footing width, the footing length, the applied pressure of the footing and the soil compressibility. Then results of the ANN model were compared with three of the most commonly used traditional methods. (Meyerhof, 1965), (Schultze and Sherif, 1973) and (Schmertmann *et al.*, 1978). The results of (Sivakugan *et al*., 1998), were confirmed by this study results, meaning that ANNs showed good ability to predict the settlement more than traditional methods. Table (3), showed that the ANNs model produced higher coefficients of correlation, r, low root mean squared errors, RMSE, and low mean absolute errors, MAE, compared with the other methods.

Table-3. Performance of ANN and traditional methods for the validation set (Shahin *et al*. 2000).

Category	ANN	Meyerhof (1965)	Schultze & Sherif (1973)	Schmertmann et al. (1978)
Correlation, r	0.99	0.33	0.86	0.70
RMSE (mm)	3.9	27.0	23.8	45.2
MAE (mm)	2.6	20.8	11.1	29.5

Similar to that, Shahin *et al*. (2002a; b; 2003a; c) applied a wide-ranging study to predict the settlement of shallow foundations on cohesionless soils using ANNs. Depending on a large database of actual measured settlements and multi-layer perceptrons (MLPs) trained with the back-propagation algorithm, Shahin *et al.* (2002b) introduced an ANN model, the five inputs were the footing width, net applied footing load, average blow count obtained from the standard penetration test (SPT) over the depth of influence of the foundations as a measure of soil compressibility, footing geometry (length to width of footing) and footing embedment ratio (embedment depth to footing width). The foundation settlement was the model output. As in Shahin et al. (2000) the results between the predicted and measured settlements obtained by utilizing ANN were compared with same three traditional methods, and Table-4 show that the ANN method better than the traditional methods for all performance measures considered.

Table-4. Performance of ANN and traditional methods for the validation set (Shahin *et al*. 2002b).

Category	ANN	**Meyerhof** (1965)	**Schultze & Sherif** (1973)	**Schmertmann *et al*. (1978)**
Correlation, r	0.905	0.440	0.729	0.798
RMSE (mm)	11.04	25.72	23.55	23.67
MAE (mm)	8.78	16.59	11.81	15.69

Furthermore, Shahin *et al*. (2002a) attempted to simplify the obtained ANN model and translated it into a tractable and relatively simple formula suitable for hand calculation.

Based on the same database, inputs and outputs, Shahin *et al.* (2003c) applied a B-spline neurofuzzy models for settlement prediction of shallow foundations on cohesionless soils. The model results then compared with the MLP model developed by Shahin *et al*. (2002b) in terms of prediction accuracy, model parsimony and model transparency. In terms of prediction accuracy, it was found that the two models were comparable, although the MLP model performs slightly better than the neurofuzzy model. In terms of model parsimony, it was found that the neurofuzzy model was more parsimonious than the MLP model with fewer model inputs and connection weights. In terms of model transparency, it was found that the B-spline model was more transparent than the MLP model, as it was able to describe the relationship between model inputs and the corresponding output in the form of a set of fuzzy rules.

Furthermore, Shahin *et al* (2005) used The ANN model that was developed by (Shahin *et al*., 2002a) to obtain deterministic settlement predictions of shallow foundations on granular soils. In this study, the likely distribution of predicted settlements, given the uncertainties associated with settlement prediction, is obtained by combining Monte Carlo simulation with a deterministic ANN model. A set of stochastic design charts, which incorporate the uncertainty associated with the ANN method, is developed. The charts are considered to be useful in the sense that they enable the designer to make informed decisions regarding the level of risk associated with predicted settlements and consequently provide a more realistic indication of what the actual settlement might be.

Rezania and Javadi (2007) presented a new genetic programming (GP) approach for predicting settlement of shallow foundations. The GP model was developed and verified using a large database of standard penetration test (SPT) based case histories that involve measured settlements of shallow foundations. The results of the developed GP model were compared with those of a number of commonly used traditional methods and artificial neural network (ANN) based models. It was showed that the GP model is able to learn, with a very high accuracy, the complex relationship between foundation settlement and its contributing factors, and render this knowledge in the form of a function. Also the authors suggested that the attained function can be used to generalize the learning and apply it to predict settlement of foundations for new cases not used in the development of the model.

Nejad and Jaksa (2010) developed an A back-propagation neural network model to predicting pile settlement based on the results of cone penetration test (CPT) data. A database containing 292 case records of actual field measurements for settlement of pile was used for model development and verification. In addition, this study discusses the choice of input and internal network parameters which were examined to obtain the optimum model. Finally, the predictions obtained by the ANN compares with those given by a number of traditional methods. The results indicate that back-propagation neural networks have the ability to predict the settlement of pile with an acceptable degree of accuracy (r=0.956, RMSE=1.06 mm) for predicted settlements ranging from 0.0 to 137.88 mm. The ANNs method has another advantage over the conventional methods in that once the model is trained, the model can be used as an accurate and quick tool for estimating the settlement of piles. In contrast with the conventional methods, the ANNs method does not need any manual work such as using tables or charts to calculate the settlement.

Results of this study indicated that ANNs have a number of significant benefits that make them a powerful and practical tool for settlement prediction of piles.

Alkroosh and Nikraz (2011) proposed the artificial neural network as an alternative to predict the load settlement behavior of pile foundations embedded in sand or mixed soils and subjected to axial loads. Three ANN models have been developed, a model for bored piles and two other models for driven piles (a model for each of concrete and steel piles). The data used for development of the ANN models is collected from the literature and include a series of in-situ piles load tests as well as cone penetration test (CPT) results. The data of each model is divided into two subsets: Training set for model calibration and independent validation set for model verification. Predictions from the ANN models are compared with the results of experimental data and with predictions of number of currently adopted load-transfer methods. Statistical analysis is used to verify the performance of the models. The results have revealed that the developed ANN models have a high capability to simulate the nonlinear behavior of soil under loads. The models also possess the ability to simulate the strain hardening behavior. The graphical and numerical comparisons between the performance of the developed models in training and validation sets indicates that the ANN models are able to forecast the load-settlement behavior accurately. The graphical illustrations of the relationship between load and settlement may indicate that the models may tend to under-predict the relationship. The graphical and numerical comparison between ANN models and the other methods demonstrates that the ANN models simulate the load-settlement behavior more accurately than the load-transfer methods. It can be concluded that the ANN models are reliable and can be applied as an alternative to forecast the load-settlement behavior for design practice.

Shahnazari *et al* (2014) utilized three new evolutionary-based techniques, including evolutionary polynomial regression (EPR), classical genetic programming (GP), and gene expression programming (GEP) to obtained more accurate predictive settlement models. The models were developed using a large databank of standard penetration test (SPT)-based case histories. The values obtained from the new models were compared with other available soft computing models, including the ANN model developed by (Shahin *et al*., 2002a; b) and the GP model developed by (Rezania and Javadi, 2007). It should be noted that the comparison between the soft computing settlement prediction models and traditional methods such as those of Meyerhof (1965), Schultze and Sherif (1973) and Schmertmann *et al.* (1978). were investigated (as mentioned above) in previous studies by Shahin *et al*. (2002a) and Rezania and Javadi (2007). The results showed that the new EPR and GP-based models are able to predict the foundation settlement on cohesionless soils under the described conditions with coefficient of determination (r2), values higher than 87%. The artificial neural networks (ANNs) and genetic programming (GP)-based models obtained from the literature, had r2 values of about 85% and 83%, respectively which are higher than 80% for the GEP-based model. A subsequent comprehensive parametric study is further carried out to evaluate the sensitivity of the foundation settlement to the effective input parameters. The comparison results proved that the new EPR and GP-based models are the most accurate models. In this study, the feasibility of the EPR, GP and GEP approaches in finding solutions for highly nonlinear problems such as settlement of shallow foundations on granular soils is also clearly illustrated. The developed models were quite simple and straightforward and can be used reliably for routine design practice.

It should be noted that, recently many researchers (as in Shahnazari *et al.*, 2014) used a coefficient of determination (r2) measure for model performance, rather than, r, so as it, (as indicated by (Das and Sivakugan, 2011+), r, sometimes may not necessarily indicate better model performance due to the tendency of the model to deviate toward higher or lower values, particularly when the data range is very wide and most of the data are distributed about their mean. Consequently, the coefficient of determination, r2, is used as it can give unbiased estimate and may be a better measure for model performance.

2.5 Load-settlement response modeling

We can saw from above, many researchers deal with soil capacity and soil settlement separately, but actually soil resistance and settlement are influenced by each other, and the design of foundations should thus consider the bearing capacity and settlement inseparably. (Shahin, 2014) used a series of full-scale in-situ pile load settlement tests and CPT data collected from the literature to develop a recurrent neural network (RNN) model for simulating the load-settlement response of drilled shafts (or bored piles). The graphical comparison of the load-settlement curves between the RNN model and experiments showed an excellent agreement and indicates that the RNN model can capture the highly non-linear load-settlement response of drilled shafts reasonably well.

2.6 Liquefaction

Earthquakes led to seismic vibrations that cause soil loss of compressive strength as a result of the soil lost its shear strength due to the increase of hydraulic pressure within pores. This ground failure phenomenon name "Liquefaction". During earthquakes liquefaction can cause ground failure and very dangerous damage to civil engineering structures. Although, the well-recognized liquefaction mechanism, the prediction of liquefaction potential is very difficult because there are many critical factors influencing liquefaction.

Many researchers were applied Artificial Neural Networks to evaluate the probability of soil liquefaction. Goh (1994b) investigated the feasibility of using neural networks to model the complex relationship between the seismic and soil parameters, and the liquefaction potential. In his study used simple back-propagation neural-network algorithm. The neural networks were trained using actual field records from 13 earthquakes that occurred in Japan, United States and Pan-America during the period 1891-1980. The model used eight input variables These variables are: the standard penetration test (SPT) value, the fines content, the mean grain size *D*50 and the maximum horizontal acceleration at ground surface with only one output variable. The output values were 1, for sites with extensive or moderate liquefaction, and for no liquefaction or marginal a value was 0. Then the results of NN model were compared with the method of (Seed *et al*., 1985). The comparison showed that the NN model was success in 95% of cases, while (Seed et al., 1985) gave a correct prediction in 84%.

Goh (1996a) used cone penetration test (CPT) resistance data to build neural networks model to measure liquefaction potential. This study data was taken from records of sand and silty sand deposits, representing five earthquakes that happened during the period 1964–1983 in Japan, China, United States and Romania. As a comparison the neural network gave a 94% success rate, which is the same number of error predictions as the conventional method by (Shibata and Teparaksa, 1988).

Najjar and Ali (1998) developed neural networks model by using field data sets of various earthquake sites from around the world to characterized the soil liquefaction resistance. The study produced a liquefaction potential valuation chart that could be useful tool for geotechnical engineers in prediction of liquefaction.

More recent Baziar and Ghorbani (2005) developed a back-propagation neural network model using professional software called STATISTICA, to predict the horizontal ground displacement in both ground slope and free face conditions due to liquefaction-induced lateral spreading. A database including 464 case histories from 10 sites located in Japan and USA (Youd *et al*, 2002)) was used for development of the model. A feed-forward network with the Levenberg- Marquardt algorithm was used in the training stage. A sensitivity analysis was also carried out to study the relative importance of the factors, affecting lateral spreading. The sensitivity analysis indicates that the two factors of source distance (R) and mean grain size (D5015) have the most significant effect on the predicted displacements while the moment magnitude of earthquake (M) and ground slope (S) have respectively moderate and small impact on displacements. The results obtained in this study indicate that the ANN model has ability to predict the lateral spreading with an acceptable degree of accuracy ($r^2$0.92, RMSE 0.7 m) for displacements ranging from 0.01 to 10.16 m. This accuracy shows the superiority of the ANN model over multilinear regression and suggests that the model can be applied in engineering practice.

Young and Byung (2006) developed a backpropagation artificial neural network model to predict the liquefaction cyclic resistance ratio (CRR) of sands using data from several laboratory studies involving undrained cyclic triaxial and cyclic simple shear testing. The model development was based on data obtained from published experimental research work available. 346 data sets relating CRR with the number of cycles (N) for liquefaction triggering. The data are for several types of sands tested under different initial conditions (269 and 77 data sets from cyclic triaxial and cyclic direct simple shear tests, respectively). The model was verified using data that was not used for training as well as a set of independent data available from laboratory cyclic shear tests on another soil. The observed agreement between the predictions and the measured CRR values indicate that the model using the basic physical properties (i.e., U_c, D_{50}, D_r, $e_{\max}$, and $e_{\min}$) is capable of effectively capturing the liquefaction resistance of a number of sands under varying initial conditions. The predicted CRR values are mostly sensitive to the variations in relative density thus confirming the ability of the model to mimic the dominant dependence of liquefaction susceptibility on soil density already known from field and experimental observations. Although the ANN methods lack fundamental linkage with the soil response from a mechanistic point of view, the results clearly demonstrated that ANN models have a strong potential and are suitable to serve as a quick interpolating/extrapolating tool for the relationship between cyclic stress ratio (CSR) and N for liquefaction.

Javadi *et al* (2006) presented genetic programming (GP) approach, for determination of liquefaction induced lateral spreading. Two general GP models were trained and validated using a database of SPT-based case histories for free face and gently sloping ground conditions. Two other specific models were presented for more accurate prediction of moderate lateral displacements of up to 1.5 m. The attained function can then be used to generalize the learning to predict liquefaction induced lateral spreading for new cases not used in the construction of the model. The results of the developed GP models are compared with those of a commonly used multi linear regression (MLR) model and the advantages of the proposed GP model over the conventional method are highlighted.

Hanna *et al* (2007) presented General Regression Neural Network (GRNN) model that addresses the collective knowledge built in simplified procedure. The model utilizes 12 soil and seismic parameters that characterize soil types, material properties, seismic characteristics, magnitude and nature of loads, and stresses and strains, strengths, saturation and seismological aspects of the soil. These parameters are real world parameters that can easily be obtained using widely accepted testing techniques and empirical formulas. The sensitivity of each of these parameters to liquefaction potential in soil was examined. In this investigation, 3,895 case records mostly from the cone penetration test (CPT) results produced from the two major earthquakes that took place in Turkey and Taiwan in 1999. Data used were randomly divided for the development, testing, and validation. Soil liquefaction decision in terms of seismic demand and seismic capacity is determined by the stress-based method and strain-based method, and further tested with the well-known Chinese criteria. The results produced by the proposed GRNN model explore effectively the complex relationship between the soil and seismic input parameters and further forecast the liquefaction potential with an overall success ratio of 94 percent. Liquefaction decisions were further validated by the SPT, confirming the viability of the SPT-to-CPT data conversion, which is the main limitation of most of the simplified methods.

Kayadelen (2011) developed four ANN models to presenting the potential of Genetic Expression Programming (GEP) and Adaptive Neuro-Fuzzy (ANFIS) computing paradigm to forecast the safety factor for liquefaction of soils. The study used data of 569 set collected from the literature. Five parameters were used as inputs such as standard penetration test ($(N1)_{60}$), percentage of finest content (FC), effective overburden stresses (σ'), cyclic stress ratios (CSR) and angle of shearing resistance (Ø'). Then the performance of models was comprehensively valuated using several statistical verification tools. Equations obtained by GEP Model and GEP Model, gave the high correlation coefficient and low RMSE values (0.18 and 0.20). On the other hand, the ANFIS models produces satisfactory results with R values ranging from 0.97 to 0.98 and RMSE values ranging from 0.27 to 0.21. The results showed that GEP and ANFIS models are fairly promising approach for the prediction of the soil liquefaction potential and capable of representing the complex relationship between seismic properties of soils and their liquefaction potential.

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Rezania *et al* (2011) developed models to represent a new approach, based on evolutionary polynomial regression (EPR), for assessment of liquefaction potential and lateral spreading. Separate EPR models were developed and tested for evaluation of liquefaction potential and lateral spreading using two different datasets of actual field case histories. A strong EPR model was developed for assessment of liquefaction potential using a large CPT database of field data. Then the models compared to those obtained from neural network and linear regression based techniques. The proposed EPR model overcome the shortcoming in the neural network-based model which it incapability to present an explicit relation- ship between input and output parameters, by generating a structured representation of the system. All EPR models have showed coefficient of determination (COD) values greater than 90%, which is a good indication of the robustness of models. Comparison of the results shows that the results predicted by the proposed EPR models provide an improvement over the ANN and MLR models. It was shown that in both cases the EPR models are able to learn, with a very high accuracy, the complex relationship between liquefaction and its contributing factors in the form of a function, and can also generalize the learning to provide predictions for new cases not used in the construction of the model. An additional advantage of the EPR approach is that there is no need to assume a priori the form of the relationship between the input and the output parameters, and the form of the relationship, the number and combination of the terms and the values of the coefficients can all be evolved during construction of the model (training). One of the strongest points of the proposed approach is that a part of the data is set aside and used for validation of the trained EPR model in order to examine the generalization capabilities of the developed model in making predictions for unseen cases.

Baziar *et al* (2014) presented a new predictive model utilizing genetic programming technique to estimate the amount of strain energy density, which is required for the liquefaction triggering of sand–silt mixtures. Model developed with a relatively large database including various types of cyclic element tests (triaxial, torsional, and simple shear) was used, gathered from previously published studies. This study selected input variables of the model from the available understandings advanced from the previous studies on the strain energy-based liquefaction potential assessment. According to the result, the amount of strain energy required for liquefaction beginning increases with increase in initial effective overburden pressure, relative density, and mean grain size. The effect of non-plastic fines on strain energy-based liquefaction resistance shows a more complex behavior. Therefore, liquefaction resistance increases with increase in fines up to about 10–15% and then starts to decline for a higher increase in fines content. Further verifications of the model were carried out using the valuable results of some downhole array data as well as centrifuge model tests. These verifications confirm that the proposed model, which was derived from laboratory data, can be successfully utilized under field conditions.

Ardakani and Kohestani (215) examined capability on of AI techniques call C4.5 decision tree for the prediction of seismic liquefaction potential of soil based on the Cone Penetration Test (CPT) data. The C4.5 model was trained and validated using a database of 109 liquefaction and non-liquefaction field case histories for sandy soils based on CPT results. The database contains the information about cone resistance (q_c), total vertical stress (σ_0), effective vertical stress (σ_0'), mean grain size (D_{50}), normalized peak horizontal acceleration at ground surface (a_{max}), cyclic stress ratio (τ/σ_0') and earthquake magnitude (M_w). The overall classification success rate for all the data set is 98%. The results of C4.5 decision tree have been compared with the available artificial neural network (ANN) and importance vector machine (RVM) models. Unlike available ANN and RVM models, the proposed model provides easily interpretable tree structure that can be used by geotechnical engineering professionals with the help of a spreadsheet to predict the liquefaction potential of soil for future seismic event without going into the complexities of model development using C4.5 decision tree. This model can be adopted for modeling different problems in geosciences.

2.7 Slope stability

Landslides or slope failures are important because they can lead to the loss of life and property. Therefore, slope stability analysis is one of the most important problems in geotechnical engineering. As most of geotechnical problems, slope failures are complex. The analysis of slope stability had been developed with the development in computational geotechnical engineering.

Limited data and unclearly defined problems often complicate the study of landslides It is very important to understanding and evaluation the behavior of the processes that govern of the slopes, in order to eliminate or reduce landslide damages. The successful performance of Artificial Neural Networks (ANNs), in modeling non-linear multivariate problems, Courage many researchers to using it in studying slope instability. (Ni et al., 1996) proposed a combining model of artificial neural networks with fuzzy sets of slopes stability evaluating. The model inputs were: horizontal profile, vertical profile, gradient, location, depth of weathering, direction of slopes, soil texture, vegetation, land use, geological origin, maximum daily precipitation and maximum hour precipitation. The slope failure potential was the output of the model. The results of the neural network showed better predicting when compared with the analytical model results.

More recent (Ferentinou and Sakellariou, 2007) applied supervised ANNs using back-propagation learning algorithm for the prediction of slope performance under static and seismic loading. Then applied unsupervised ANNs using the efficient visualization techniques offered by self-organizing maps in lithological classification of unsaturated soils and in classification of dry and wet slopes according status of stability and failure mechanism.

The study finally proposed a coupled model of SOM ANN with interaction matrix in order to rate slope stability controlling variables. The work concluded that the application of computational intelligence tools on the real-world data sets using both supervised and unsupervised methods gave reasonable results.

Cho (2009) presented a practical procedure that combined a commercial numerical analysis code and artificial neural networks into the probabilistic analysis of slope stability. An ANN technique was adopted to establish a model for the approximation of the limit state function. Training and test data sets for the model were obtained from numerical calculations based on the strength reduction method. Then the ANN model connected to a reliability method, in this case the first- and second order reliability method and the Monte Carlo simulation method, to predict the failure probability. The obtained results also showed that the ANN-based response surface can be successfully applied to the problem of probabilistic slope stability.

Chauhana *et al* (2010) proposed a new approach for landslide susceptibility zonation (LSZ) mapping based on the ratings of categories of causative factors derived from an ANN model. These ratings depicted the specific individual influence of each category on landslide incidents. The study was conducted in a landslide prone area in the Himalayan Region. Seven causative factors, namely: slope, slope aspect, relative relief, lithology, structural features (e.g., thrusts and faults), land use/ land cover, and drainage density, were placed in 42 categories for which ratings were determined. The structural buffer category 0–500 m, with the highest rating of 376.5m, was found to be the most influential among the 42 categories. The evaluation of LSZ mapping through landslide density analysis, best-fit quadratic curves and receiver operating curves (ROC), clearly demonstrated the efficiency of the proposed approach and provided an accurate representation of the actual scenario of landslide occurrences in the study region.

Gemitzi *et al* (2011) presented a methodology for landslide susceptibility assessment to delineate landslide prone areas by using factor analysis and fuzzy membership functions and Geographic Information Systems (GIS). Six conditioning factors were evaluated: slope angle, slope aspect, land use, geology, distance to faults and topographical elevation. Fuzzy membership functions were defined for each factor using the landslide frequency data. Factor analysis provided weights (i.e., importance for landslide occurrences) for each one of the above conditioning factors, indicating the most important factors as geology and slope angle. An overlay and index method was adopted to produce the landslide susceptibility map. In this map 96% of the observed landslides are located in very high and high susceptibility zones, indicating a suitable approach for landslide susceptibility mapping.

Das *et al* (2011) discussed the application of two different types of ANN models as alternate tools to classify the slope as stable (1) or failed (0) and to predict the factor of safety. The database available in Sah *et al.* (1994) has been used. The database consists of case studies of 23 dry and 23 wet slopes where 29 are failed and 17 are stable slopes. The input data consist of parameters like height of slope H (m), unit weight γ (kN/m3), cohesion c (kPa), internal friction angle ϕ (˚), slope angle β (˚) and pore pressure parameters ru. Yang *et al*. (2004) have used the above database to develop prediction model using genetic programming (GP). The output database consists of qualitative information classifying the slope as stable or failed and quantitative information that consists of factor of safety of the slope based on limit equilibrium method. The ANN models were trained using Bayesian regularization (BRNN), differential evolution algorithm (DENN) and commonly used Levenberg–Marquardt (LMNN), and the results are compared with those from support vector machine and genetic programming available in literature. The results of DENN are found to better than most likelihood method and comparable to that of GP. Applying sensitivity analysis to identify important input parameters, based on DENN model, C is found to most important parameter followed by ϕ, β, γ, H and ru. As these are circular failure surfaces, C should be the most important parameters followed by ϕ, and β. Hence, it may be concluded that the results of DENN model better represents the physical problem.

Peng *et al* (2014) presented a systematic method for slope safety evaluation utilizing multi-source monitoring information. First, a Bayesian network with continuously distributed variables for a slope involving the factor of safety, multiple monitoring indexes and their influencing parameters (e.g. friction angle and cohesion) is constructed. Then the prior probabilities for the Bayesian network are quantified considering model and parameter uncertainties. After that, multi-source monitoring information is used to update the probability distributions of the soil or rock model parameters and the factor of safety using Markov chain Monte Carlo simulation. The study concluded that he method is able to integrate multi-source information based on slope stability mechanisms, and update the soil or rock parameters, the slope factor of safety, and the failure probability with the integrated monitoring information. Hence the evaluation becomes more reliable with the support of multiple sources of site-specific information.

2.8 Earth retaining structures

The bracing of excavation is one of the important matter in geotechnical engineering, could be temporary during the construction stage, or permanent as in underground structures or that adjacent to soil ramp. Goh *et al*., 1995d) utilizing a neural network model for initial estimates of maximum wall deflections for braced excavations in soft clay. The model used as input parameters: the height of excavation, the excavation walls stiffness, excavation width, soil unit weight soil, thickness/excavation width ratio, soil undrained shear strength and undrained soil modulus/shear strength ratio. The output of the model was the maximum wall deflection. The regression analysis the scatter of the predicted neural network deflections, used as a relative to the deflections obtained using the finite element method.

Results showed high coefficients of correlation for the training and testing data of 0.984 and 0.967, respectively. Furthermore, some actual case records data were used to confirm the performance of the trained neural network model. The agreement of the neural network predicted and measured wall deflections was promising. The study proposed to use the neural network model as a time-saving and easy to use, as alternative to the finite element method.

More recent (Goh and. Kulhawy, 2005) demonstrates the use of an integrated neural network–reliability method to assess the risk of serviceability failure through the calculation of the reliability index. In this study applied a series of parametric studies using the finite element method and then approximating the non-linear limit state surface (the boundary separating the safe and 'failure' domains) through a neural network model, the reliability index can be determined with the aid of a spreadsheet. Although, descriptive examples are presented to show how the serviceability performance for braced excavation problems can be assessed using the reliability index.

Gordon *et al* (2007) presented an artificial neural network methodology for predicting deflection of diaphragm walls caused by braced excavation in soft to medium clays. The ANN model input variables were, excavation depth, system stiffness, excavation width, shear strength normalized with vertical effective stress, and Young's modulus normalized with vertical effective stress. The maximum wall deflection in a braced excavation in soft to medium clays was the output of model. The database for training and testing the ANN is generated from hypothetical cases using finite element method. The performance of the developed ANN reveals that the influence of each input variable on the wall deflection is consistent with the excavation behaviors generally observed in the field. The validation using 12 excavation case histories collected in this study shows that the wall deflection caused by braced excavation can be accurately predicted by the developed ANN.

2.9 Tunnels and underground openings

Shi *et al.* (1998) applied neural networks to predict settlements of tunnels. The study used data from the 6.5 km Brasilia Tunnel, Brazil, to training and testing the model using. The model inputs and three settlement parameters as the model outputs. The input parameters were, the length of excavation from drive start, the depth of soil cover above tunnel crown, the area of tunnel section, the delay for closing invert, the water level depth, the rate of advance of excavation, the construction method, the mean blow count from standard penetration test at tunnel crown level, the mean blow count from standard penetration test at tunnel spring-line level and the mean blow count from standard penetration test at tunnel inverted arch level. The outputs were the settlement at the face passage, the settlement at the invert closing and the final settlement after stabilization. This study results indicated low level of accuracy was obtained from the neural network model. Then study proposed a modular neural network model based on the concept of integrating multiple neural network modules in one system, in order to improve the prediction accuracy, with each module being constrained to operate at one specific situation of a complicated real world problem. The modular concept showed an improvement in terms of model convergence and prediction. (Shi, 2000) developed the models to improve the capability by applying input data transformation. This extended study indicated that distribution transformation of the input variables reduced the prediction error by more than 13%.

Haji hassani *et al* (2011) used a Back propagation neural network model A Back propagation neural network modelling was used to predict surface settlement due to NATM tunneling techniques in soft ground. For model training and verification, 24 data sets containing field measurement data ware used. The inputs were including the standard penetration test (SPT), moisture content, cohesion, tunnel depth, frictional Angle, unit Weight, Poisson Ratio, elasticity modulus. While the model outputs were the surface settlement at several points. To obtain the optimal ANN architecture, several models were investigated and finally a model with one hidden layer with 20 nodes was chosen. The results manifest that the Back propagation neural networks are capable of predicting the surface settlement due to NATM tunneling in soft ground with adequate accuracy.

Juwaied and Al-ZwainyA, (2017) utilizing database of 63 historical cases collected from five projects in Iraq/Baghdad to be the reference to produce of pile design equation. The resulting equation was used to find the prediction design load of the pile and compare it with the actual. The results showed relatively high correlation coefficient r, 96% between the actual and predicted values., as well as the results showed high correlation coefficient r,97% and coefficient of determination r^2, 94% between the actual and predicted values, for the 7 cases not used in the model development.

3. CONCLUSIONS

Through the above review and discussion, the success of artificial intelligence applications has been demonstrated in geotechnical engineering. Based on the results of the research above, it can be said that artificial intelligence techniques have performed better than or at least approximated conventional methods.

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Table-5. Summary of some applications of AI techniques in geotechnical engineering.

No	Researchers	Data collection methods	Techniques	Results
1	Pile driving records Reanalyzed using neural networks			
	Goh 1996	Actual pile driving records	Back Propagation Neural Networks	They indicated that the neural network predictions are more reliable than the conventional pile driving formulae
2	Application of an Artificial Neural Network for Analysis of Subsurface Contamination at the Schuyler Falls Landfill, NY			
	Rizzo and Dougherty 1996	Historical Data	Artificial Neural Networks	Applied and tested a new pattern method on a variety of site characterization problems, called it “SCANN” (Site characterization using Artificial Neural Networks), Unlike the kriging methods, SCANN is data-driven and requires no estimation of a covariance function. It uses a feed-forward counter propagation training approach to determine a "best estimate" or map of a discrete spatially-distributed field.
3	Prediction of Pile Bearing Capacity Using Artificial Neural Networks			
	Lee and Lee 1996	In situ pile load tests obtained from a literatures	Error Back Propagation Neural Networks	The results showed that the neural networks predicted values corresponding the measured values much better than those obtained from Meyerhof’s equation.
4	General regression neural networks for driven piles in cohesionless soils			
	Abu-Kiefa 1998	Historical Data	General Regression Neural Network	Concluded that the GRNNM is applicable for all different conditions of driven piles in cohesionless soils.
5	Prediction of Pile Capacity Using Neural Networks			
	Teh *et al.* 1997	Historical Data	Back propagation neural networks	The study showed that the neural network model predicted the total capacity reasonably well. The neural-network-predicted soil resistance along the pile was also in general agreement with the CAPWAP solution.
N°	**Researchers**	**Data collection Methods**	**Techniques**	**Results**
6	Subsurface Characterization Using Artificial Neural Network And Gis			
	Gangopadhyay *et al.*, 1999	Historical Data	Multilayer perceptron using the back-propagation algorithm	The integrated approach of ANN and GIS, is shown to be a powerful tool for characterizing complex aquifer geometry, and for calculating aquifer parameters for ground-water flow modeling.
7	Artificial intelligence techniques for the design and analysis of deep foundations			
	Nawari *et al.*, 1999	Historical Data	NN, and Generalized Regression Neural Network	Based on the results from this investigation, it appeared that the proposed neural network models furnish a pragmatic and a reliable alternative for the current analysis and design techniques of axial pile capacity and laterally loaded piles.
8	Bayesian Neural Network Analysis of Undrained Side Resistance of Drilled Shafts			
	Goh *et al.*, 2005	Historical Data	Bayesian neural network algorithm	The developed neural network model provided good estimates of the undrained side resistance adhesion factor. Furthermore, one distinct benefit of this neural network model is the computation of the error bars on the predictions of the adhesion factor. These error bars will aid in giving confidence to the predicted values and the interpretation of the results.
9	Undrained Lateral Load Capacity of Piles in Clay Using Artificial Neural Network			
	Das and	Historical Data	Back propagation	The developed ANN model is more efficient

	Basudhar, 2006		neural networks	compared to empirical models of Hansen and Broms.
10	Prediction of Friction Capacity of Driven Piles In Clay Using The Support Vector Machine			
	Samui, 2008	Data Base	SVM	With the database collected by Goh (1995) the study shows that SVM has the potential to be a useful and practical tool for prediction of friction capacity of driven piles in clay.
11	Modelling Pile Capacity Using Gaussian Process Regression			
	Pal and Deswal 2010	Actual pile-driving records in cohesion-less soil	Gaussian Process (GP) Regression and SVM	The GP regression approach works well in predicting the load-bearing capacity of piles as compared to the SVM approach. Another conclusion from this study is that the Pearson VII function kernel performs well in comparison to the radial basis function kernel with both GP- and SVM-based approaches to model the pile capacity. The results of this study also suggest that GP regression works well as compared to the empirical relations in predicting the ultimate pile capacity.
12	Prediction of Pile Settlement Using Artificial Neural NetworksBased on Cone Penetration Test Data			
	Nejad and Jaksa 2010	Database	Back-propagation neural network	The results indicate that back-propagation neural networks have the ability to predict the settlement of pile with an acceptable degree of accuracy (r=0.956, RMSE=1.06 mm) for predicted settlements ranging from 0.0 to 137.88 mm.
13	Intelligent Computing for Modeling Axial Capacity of Pile Foundations			
	Shahin 2010	Historical Data	Artificial Neural Network (ANN)	The results indicate that the ANN models were capable of accurately predicting the ultimate capacity of pile foundations, and compare well with what one would expect based on available geotechnical knowledge and experimental results.
No	**Researchers**	**Data collection Methods**	**Techniques**	**Results**
14	Neural Network Model for Predicting the Resistance of Driven Piles			
	Park and Cho 2010	data from dynamic piles load test	Artificial Neural Network (ANN)	The results showed that the ANN model served as a reliable and simple predictive tool to predict the resistance of the driven pile with correlation coefficient values close to 0.9.
15	Neural Network Application in Prediction of Axial Bearing Capacity of Driven Piles			
	Harnedi and Kassim 2013	Pile Driving Analyzer (PDA)	Artificial Neural Network (ANN)	The results showed that the neural network models give a good prediction of axial bearing capacity of piles if both stress wave data and properties of both driven pile and driving system are considered in the input data.
16	Application of Artificial Neural Network for Predicting Shaft and Tip Resistances of Concrete Piles			
	Momeni *et al.*, 2015	Pile Driving Analyzer (PDA)	Artificial Neural Network (ANN)	Founded that a network with five hidden nodes in one hidden layer yields the best performance. Additionally, through a sensitivity analysis, it was founded/ that the pile length and cross sectional area are the most influential parameters in predicting the bearing capacity of piles
17	Analysis of Ultimate Bearing Capacity of Single Pile Using the Artificial Neural			

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	Wardani *et al*., 2013	Full-Scale Pile Load Test and SPT	Artificial Neural Network (ANN)	The results showed that neural networks can be used for prediction of ultimate bearing capacity of single pile foundation and the model have the highest performance among the other methods, even though the difference is not too big.
18	ANN Prediction of Some Geotechnical Properties of Soilfrom their Index Parameters			
	Tizpa et. al 2014	Database	artificial neural network	Comparison between the results of the developed models and experimental data indicated that predictions are within a confidence interval of 95 %. According to the performed sensitivity analysis, Atterbeg limits and the soil fine content (silt+clay) are the most important variables in predicting the maximum dry density and optimum moisture content.
19	Load–settlement modeling of axially loaded steel driven piles using CPT-based recurrent NNs			
	Shahin 2014a	Pile Load Tests, and (CPT) Data	Recurrent neural network (RNN)	Founded that the developed RNN model has the ability to reliably predict the load–settlement response of axially loaded steel driven piles, and thus, can be used by geotechnical engineers for routine design practice.
20	Evolutionary-Based Approaches for Settlement Prediction of Shallow Foundations on Cohesionless Soils			
	Shahnazari et. al 2014	Historical Data	Polynomial regression, genetic programming (GP), & gene expression programming (GEP)	In this study, the feasibility of the EPR, GP and GEP approaches in finding solutions for highly nonlinear problems such as settlement of shallow foundations on granular soils is also clearly illustrated
21	State-of-the-Art Review of Some Artificial Intelligence Applications in Pile Foundations			
	Shahin 2014b	Historical Data	Artificial intelligence	AI techniques perform better than, or at least as good as, the most traditional methods.
No	**Researchers**	**Data collection Methods**	**Techniques**	**Results**
22	Artificial Neural Network Model for Prediction of Bearing Capacity of Driven Pile			
	Maizir et. al 2015	Pile Driving Analyzer (PDA) test data	Artificial Neural Network	The results show that the ANN model serves as a reliable prediction tool to predict the resistance of the driven pile with coefficient of correlation (R) values close to 0.9 and mean squared error (MSE) less than 1% .
23	Toward improved prediction of the bedrock depth underneath hillslopes: Bayesian inference of the bottom-up control hypothesis using high-resolution topographic data			
	Gomes *et al*. 2016	High-resolution topographic data	Numerical modeling, and Bayesian analysis	The results demonstrate that the proposed DTB model with lumped parameters mimics reasonably well the observed regolith depth data with root mean square error (RMSE).
24	Determination bearing capacity of driven piles in sandy soils using Artificial Neural Networks			
	Mazaher and Berneti 2016	Database	MLP Neural Network	The NN has very high efficiency in predicting load carrying capacity of metal piles, and it is concluded that soil internal friction angle, soil elastic modulus, pile diameter and pile length respectively have maximum effect on load carrying capacity of piles.

REFERENCES

A. Ardakanivand V. R. Kohestani. 2015. Evaluation of liquefaction potential based on CPT results using C4.5 decision tree. Ardakani & Kohestani/ Journal of AI and Data Mining.

Abu-Kiefa M. A. 1998. General regression neural networks for driven piles in cohesionless soils. J. Geotech. Geoenv. Engrg. ASCE, Vol. 123.

Adel M. Hanna, Derin Ural, Gokhan Saygili. 2007. Evaluation of liquefaction potential of soil deposits using artificial neural networks. Engineering Computations: International Journal for Computer-Aided Engineering and Software. Vol. 24.

Agrawal G., Weeraratne S., and Khilnani K. 1994. Estimating clay liner and cover permeability using computational neural networks. Proc., First Congress on Computing in Civil Engrg., Washington, June.

Ahmadreza Mazaher and Mazaher Berneti. 2016. Determination bearing capacity of driven piles in sandy soils using Artificial Neural Networks (ANNs). IOSR Journal of Mechanical and Civil Engineering.

Akbar A. Javadi Mohammad Rezania Mohaddeseh Mousavi Nezhad. 2006. Evaluation of liquefaction induced lateral displacements using genetic programming. Computers and Geotechnics.

Alkroosh I., Nikraz H. 2011. Simulating pile load-settlement behavior from CPT data using intelligent computing. Central European Journal of Engineering.

Alsamman, O.M., 1995. The Use of CPT for Calculating Axial Capacity of Drilled Shafts. PhD Thesis. University of Illinois-Champaign, Urbana, Illinois.

American Petroleum Institute. RP2A: Recommended practice for planning, designing and constructing fixed offshore platfonns, 15th Ed. 1984.

Arnold M. A. 1999. Artificial neural networks applied to the prediction of settlements of shallow foundations in granular soils. MEngSc. thesis, James Cook University, Queensland.

Basheer I. A., Reddi, L. N. and Najjar Y. M. 1996. Site characterisation by neuronets: An application to the landfill siting problem. Ground Water.

Briaud J. L. & Tucker L. M. 1988. Measured and predicted axial capacity of 98 piles. ASCE, Journal of Geotechnical Engineering. 114(9).

Broms B. B. and Lim P. C. 1988. A simple pile driving formula based on stress-wave measurements. Proc. 3rd Int. Conf. on the Application of Stress-Wave Theory to Piles.

Burland J. B. 1973. Shaft friction of piles in clay. Ground Engineering.

C. Kayadelen. 2011. Soil liquefaction modeling by Genetic Expression Programming and Neuro-Fuzzy. Expert Systems with Applications 38.

Cal Y. 1995. Soil classification by neural-network. Advances in Engineering Software.

Chan W.T., Chow Y.K., Liu L.F. 1995. Neural network: an alternative to pile driving formulas. Computers and Geotechnics.

Cho S.E. 2009. Probabilistic stability analyses of slopes using the ANN-based response surface, Computers and Geotechnics. Vol. 36.

Djajaputra A. A. 1997. Konsep Beban Terfaktor Dalam Perancangan Tiang Bor, Proceeding Seminar PILE'97.

Ellis G.W.; Yao, C; Zha o R. & Penumadu D. 1996. Stress–strain modeling of sands using artificial neural networks, J Geotech Eng. Vol. 121.

Elshorbagy A., Corzo G., Srinivasulu S., Solomatine D.P., 2010. Experimental investigation of the predictive capabilities of data driven modeling techniques in hydrology-part 1: concepts and methodology. Hydrology and Earth System Science.

Eslami A. & Fellenius B. H. 1996. Pile capacity by direct CPT and CPTu methods applied to 102 case histories. Canadian Geotechnical Journal.

Eslami A. 1996. Bearing capacity of piles from cone penetration test data. Ph.D. thesis, University of Ottawa, Ottawa, Ont.

F. Pooya Nejad; Mark B. Jaksa. 2010. Prediction of Pile Settlement Using Artificial Neural Networks Based on Cone Penetration Test Data. Advances in Analysis, Modeling & Design. 2010 ASCE.

F. Pooya Nejad; Mark B. Jaksa. 2010. Prediction of Pile Settlement Using Artificial Neural Networks Based on Cone Penetration Test Data. Advances in Analysis, Modelling & Design. 2010 ASCE.

Ferentinou M.D. & Sakellariou M.G. 2007. Computational intelligence tools for the prediction of slope performance, Computers and Geotechnics.

Flaate K. S. 1964. An investigation of the validity of three pile drivingformulae in cohesionless material. Norwegian Geotech. Inst., Oslo, Norway.

Gemitzi Falalakis, Eskioglou Petalas. 2011. Evaluating Landslide Susceptibility Using Environmental Factors, Fuzzy Membership Functions and Gis. Global Nest Journal.

Ghaboussi J. and Sidarta D. E. 1997. New nested adaptive neural networks (NANN) for constitutive modeling. J. Computers and Geotechnics.

Goble G. G., Likins G. E. and Rausche F. 1975. Bearing capacity of piles from dynamic measurements. Final Report, Dept. of Civil Eng., Case Western University.

Goh A. T. C. 1994a. Nonlinear modelling in geotechnical engineering using neural networks. Australian Civil Engineering Transactions.

Goh A. T. C. 1994a. Nonlinear modelling in geotechnical engineering using neural networks. Australian Civil Engineering Transactions.

Goh A. T. C. 1994b. Seismic liquefaction potential assessed by neural network. J. Geotech. & Geoenv. Eng., 120.

Goh A. T. C. 1995a. Back-propagation neural networks for modeling complex systems. Artificial Intelligence in Engineering.

Goh A. T. C. 1995a. Back-propagation neural networks for modeling complex systems. Artificial Intelligence in Engineering.

Goh A. T. C. 1995b. Empirical design in geotechnics using neural networks. Geotechnique.

Goh A. T. C. 1995c. Modeling soil correlations using neural networks."J. Computing in Civil Eng., ASCE.

Goh A. T. C. 1996a. Neural-network modeling of CPT seismic liquefaction data. J. Geotech. Engrg., ASCE
Goh A. T. C. 1996b. Pile driving records reanalyzed using neural networks. J. Geotech. Eng.

Goh A. T. C., Wong K. S. and Broms B. B. 1995d. "Estimation of lateral wall movements in braced excavation using neural networks. Canadian Geotech

Goh A. T. C.; Fred H. Kulhawy, F. ASCE; and C. G. Chua. 2005. Bayesian Neural Network Analysis of Undrained Side Resistance of Drilled Shafts 10.1061/ (ASCE)1090.

Goh A.T., Kulhawy F.H., Chua C.G. 2005. Bayesian neural network analysis of undrained side resistance of drilled shafts. J. Geotech. Geoenviron. Eng.

Gordon T.C. Kung, Evan C.L. Hsiao, Matt Schuster, C. Hsein Juang. 2007. A neural network approach to estimating deflection of diaphragm walls caused by excavation in clays. Computers and Geotechnics.

Gribb M. M. and Gribb G. W. 1994. Use of neural networks for hydraulic conductivity determination in unsaturated soil. Proc., 2nd Int. Conf. Ground Water Ecology, J. A. Stanford and H. M. Valett, eds., Bethesda MD: Amer, Water Resources Assoc.

Griffith D.V., G.A. Fenton, N. Manoharan. 2002. Bearing Capacity of Rough Rigid Strip Footing on Cohesive Soil: Probability Study, Journal of Geotechnical and Geoenvironmental Engineering.

Guilherme J. C. Gomes, Jasper A. Vrugt and Eurfipedes A. Vargas Jr. 2016. Toward improved prediction of the bedrock depth underneath hillslopes: Bayesian inference of the bottom-up control hypothesis using high-resolution topographic data. Water Resources Research.

H. Shahnazari M.A. Shahin and M.A. Tutunchian1. 2014. Evolutionary-based approaches or settlement prediction of shallow foundations on cohesionless soils. International Journal of Civil Engineering, Vol. 12, No. 1, Transaction B: Geotechnical Engineering, January.

Hajihassani M., Marto A., Nazmi E., Abad S., Shahrbabaki, M. 2011. Prediction of surface settlements induced by NATM tunneling based on artificial neural networks. Electro. J. Geotech. Eng.

Harnedi Maizir, Nurly Gofar and Khairul Anuar Kassim. 2015. Artificial Neural Network Model for Prediction of Bearing Capacity of Driven Pile. Jurnal Teoretis dan Terapan Bidang Rekayasa Sipil.

Hiley A. 1922. The efficiency of the hammer blow, and its effects with reference to piling. Engineering,

Hyun U. Park. 2011. Study for Application of Artificial Neural Networks in Geotechnical Problems, Artificial Neural Networks - Application, Dr. Chi Leung Patrick Hui (Ed.).

Hyun U. Park & Cho, C.H. 2010. Neural Network Model for Predicting the Resistance of Driven Piles Marine Geosources and Geotechnology, In Press.

Jaksa, M. B. 1995. The influence of spatial variability on the geotechnical design properties of a stiff, over consolidated clay, PhD. thesis, The University of Adelaide, Adelaide.

Janbu N. 1953. Une analyse energetique du battage des pieux a l'aide de parametres sans dimension. Norwegian Geotech. Inst., Oslo, Norway.

Juwaied Nabeel S. and Faiq M.S. Al-Zwainy. 2017. Pile Design Using Multiple Linear Regression Model. ARPN Journal of Engineering and Applied Sciences. 12(15).

Kim Young-Su and Kim Byung. 2006. Use of Artificial Neural Networks in the Prediction.

L.E. Besawa, D.M. Rizzob and P.J. Mouserb. 2006. Application of an Artificial Neural Network for Analysis of Subsurface Contamination at the Schuyler Falls Landfill, NY.

Lee I. M. and Lee J. H. 1996. Prediction of pile bearing capacity using artificial neural networks. Computers and Geotechnics.

M. Peng, X.Y. Li, D.Q. Li, S.H. Jiang, L.M. Zhang. 2014. Slope safety evaluation by integrating multi-source monitoring information. Structural Safety.

M.H. Baziar, A. Ghorbani. 2005. Evaluation of lateral spreading using artificial neural networks. Soil Dynamics and Earthquake Engineering.

Meyerhof G. G. 1965. Shallow foundations. J. Soil Mech. & Found. Div.

Meyerhof G. G. 1965. Shallow foundations. J. Soil Mech. & Found. Div.

Meyerhof G. G. 1976. Bearing capacity and settlement of pile foundations. J. Geotech. Eng.

Mohammad H.Baziar, Yase Jafarian, Habib Shahnazari, Vahid Movahed, Mohammad Amin Tutunchian. 2014. Prediction of strain energy-based liquefaction resistance of sand-silt mixtures: An evolutionary approach. Computers & Geosciences.

Mohammad Rezania, Asaad Faramarzi, AkbarA. Javadi. 2011. An evolutionary based approach for assessment of earthquake-induced soil liquefaction and lateral displacement. Engineering Applications of Artificial Intelligence.

Najjar Y. M. and Ali H. E. 1998. CPT-based liquefaction potential assessment: A neuronet approach. Geotechnical Special Publication, ASCE.

Najjar Y. M. and Basheer I. A. 1996a. Utilizing computational neural networks for evaluating the permeability of compacted clay liners. Geotechnical and Geological Engineering.

Najjar Y. M. and Basheer I. A. 1996b. Utilizing computational neural networks for evaluating the permeability of compacted clay liners. Geotechnical and Geological Engineering.

Najjar Y. M., Basheer I. A. and Naouss W. A. 1996b. On the identification of compaction characteristics by neuronets. J. Computers and Geotechnics.

Nawari N. O., Liang R. and Nusairat J. 1999. Artificial intelligence techniques for the design and analysis of deep foundations. Elec. J. Geotech. Eng.

Ni S.H.; Lu P.C. & Juang C.H. 1996. A fuzzy neural network approach to evaluation of slope failure potential, Journal of Microcomputers in Civil Engineering.

Parichehr Tizpa, Reza Jamshidi Chenari, Mehran Karimpour Fard, Sandro Lemos achado. 2014. ANN prediction of some geotechnical properties of soil from their index parameters. Arab J Geosci.

Penumadu D. and Jean-Lou C. 1997. Geomaterial modeling using artificial neural networks. Artificial Neural Networks for Civil Engineers: Fundamentals and Applications, ASCE.

Penumadu D. and Jean-Lou C. 1997. Geomaterial modeling using artificial neural networks. Artificial Neural Networks for Civil Engineers: Fundamentals and Applications, ASCE.

Penumadu D. and Zhao R. 1999. Triaxial compression behavior of sand and gravel using artificial neural networks (ANN). J. Computers and Geotechnics.

Penumadu D., Jin-Nan L., Chameau J.-L. and Arumugam S. 1994. Rate dependent behavior of clays using neural.

Pijush Samui. 2012. Three-Dimensional Site Characterization Model of Bangalore Using Support Vector Machine. International Scholarly Research Network ISRN Soil Science.

Rahman M.S. and M. Mulla. 2005. Fuzzy Neural Network Models for Geotechnical Problems, NCDOT Research Project, USA.
Randolph M. F. 1985. Capacity of piles driven into dense sand. Rep. Soils TR 171, Engrg. Dept., Cambridge University, Cambridge.

Randolph M. F. and Wroth C. P. 1978. Analysis of deformation of vertically loaded piles. J. Geotech. Eng.

Rausche F., Moses F. and Goble G. G. 1972. Soil resistance predictions from pile dynamics. J. Soil Mech. and Found. Div.

Rausche F., Moses F. and Goble G. G. 1972. Soil resistance predictions from pile dynamics. J. Soil Mech. and Found. Div.

Rezania M, Javadi A.A. 2007. A new genetic programming model for predicting settlement of shallow foundations. Canadian Geotechnical Journal.

Rezania M, Javadi A.A. 2007. A new genetic programming model for predicting settlement of shallow foundations, Canadian Geotechnical Journal.

Rizzo D. M. and Dougherty D. E. 1994. Application of artificial neural networks for site characterization using hard and soft information. Proc., 10th Int. Conf. Computational Methods in Water Resources.

Romero S. and Pamukcu S. 1996. Characterization of granular meterial by low strain dynamic excitation and ANN. Geotechnical Special Publication, ASTM-ASCE.

S. Banu Ikizler, Mustafa Vekli, Emrah Dogan, Mustafa Aytekin, Fikret Kocabas. 2012. Prediction of swelling pressures of expansive soils using soft computing methods. Neural Comput & Applic.

S. Banu Ikizler, Mustafa Aytekin, Mustafa Vekli, Fikret Kocabas. 2009. Prediction of swelling pressures of expansive soils using artificial neural networks. Advances in Engineering Software.

Sarat Kumar Das, Rajani Kanta Biswal, N. Sivakugan, Bitanjaya Das. 2011. Classification of slopes and prediction of factor of safety using differential evolution neural networks Environ Earth Sci.

Schmertmann J. H. 1970. Static cone to compute static settlement over sand. J. Soil Mech. & Found.

Schmertmann J. H., Hartman J. P. and Brown P. B. 1978. Improved strain influence factor diagrams. J.Geotech. Eng.

Schultze E and Sherif G. 1973. Prediction of settlements from evaluated settlement observations for sand. Proc. 8th Int. Conf. Soil Mechan. & Found. Eng.

Schultze E. and Sherif, G. 1973. Prediction of settlements from evaluated settlement observations for sand. Proc. 8th Int. Conf. Soil Mechan. & Found. Eng.

Seed H.D., Tokimatsu K., Harder L. F. and Chung R. M, 1985. Influence of SPT procedure in soil liquefaction resistance evaluation Journal of Geotechnical Engineering. ASCE.

Semple R. M. and Rigden W. J. 1986. Shaft capacity of driven pipe piles in clay. Ground Engineering.

Shahin M. 2014a. Load-settlement modelling of axially loaded drilled shafts using CPT-based recurrent neural networks. International Journal of Geomechanics.

Shahin M. A 2010. Intelligent computing for modeling axial capacity of pile foundations. Canadian Geotechnical Journal.

Shahin M. A., Jaksa M. B. and Maier H. R. 2000. Predicting the settlement of shallow foundations on cohesionless soils using back-propagation neural networks. Research Report No. R 167, The University of Adelaide,

Shahin M. A., Jaksa M. B. and Maier H. R. 2002a. Artificial neural network-based settlement prediction formula for shallow foundations on granular soils. Australian Geomechanics.

Shahin M. A., Jaksa M. B. and Maier H. R. 2003a. Neurofuzzy networks applied to settlement of shallow foundations on granular soils. 9th Int. Conf. on Applications of Statistics and Probability in Civil Eng.

Shahin M. A., Maier H. R. and Jaksa M. B. 2002b. Predicting settlement of shallow foundations using neural networks. J. Geotech. & Geoenv. Eng.

Shahin M. A., Maier H. R. and Jaksa M. B. 2002b. Predicting settlement of shallow foundations using neural networks. J. Geotech. & Geoenv. Eng.

Shahin M. A., Maier H. R. and Jaksa M. B. 2003c. Neural and neurofuzzy techniques applied to modelling settlement of shallow foundations on granular soils. Int. Congress on Modelling and Simulation.

Shahin M. A., Maier H. R. and Jaksa M. B. 2003c. “Neural and neurofuzzy techniques applied to modelling settlement of shallow foundations on granular soils. Int. Congress on Modelling and Simulation.

Shahin M.A.; Jaksa M.B. & Maier H.R. 2005. Stochastic simulation of settlement prediction of shallow foundations based on a deterministic artificial neural network.

Shi J. J. 2000. Reducing prediciton error by transforming input data for neural networks. J. Computing in Civil Engrg., ASCE.

Shi J., Ortigao J. A. R. and Bai J. 1998. Modular neural networks for predicting settlement during tunneling. J.Geotech. & Geoenv. Engrg., ASCE.

Shibata T. and Teparaksa W. 1988. Evaluation of liquefaction potentials of soils using cone penetration tests. Soils and Foundations.

Shivani Chauhana, Mukta Sharmab, M.K. Aroraa, N.K. 2010. Guptac Landslide Susceptibility Zonation through ratings derived from Artificial Neural Network. International Journal of Applied Earth Observation and Geoformation.

Sivakugan N., Eckersley J. D. and Li H. 1998. Settlement predictions using neural networks. Australian Civil Engineering Transactions.

Sivakugan N., Eckersley J. D. and Li H. 1998. Settlement predictions using neural networks. Australian Civil Engineering Transactions.

Subhrendu Gangopadhyay, Tirtha Raj Gautam, and Ashim Das Gupta. 1999. Subsurface Characterization Using

Artificial Neural Network and Gis. Journal of Computing in Civil Engineering.

Teh C. I., Wong K. S., Goh A. T. C. and Jaritngam S. 1997. Prediction of pile capacity using neural networks. J. Computing in Civil Eng.

Terzaghi K. and Peck R. 1967. Soil mechanics in engineering practice, John Wiley & Sons, New York.

Wardani S.P.R., Surjandari N.S., Jajaputra A.A. 2013. Analysis of Ultimate Bearing Capacity of Single Pile Using the Artificial Neural. Proceedings of the 18th International Conference on Soil Mechanics and Geotechnical Engineering, Paris 2013.

Wellington A. M. 1892. The iron wharf at Fort Monroe, Va. ASCE Transactions.

Yongjei Lee, Sungchil Lee, and Hun-Kyun Bae. 2014. Design of Jetty Piles Using Artificial Neural Networks. Hindawi Publishing Corporation the Scientific World Journal Volume.

Youd TL, Hansen CM, Bartlett SF. 2002. Revised multilinear regression equations for prediction of lateral spread displacement. J Geotech Geoenviron Eng; ASCE. 128.

Zhou Y. and Wu X. 1994. Use of neural networks in the analysis and interpretation of site investigation data. Computer and Geotechnics.

Zhu J. H., Zaman M. M. and Anderson S. A. 1998a. Modeling of soil behavior with a recurrent neural network. Canadian Geotech. J.

Zhu J. H., Zaman M. M. and Anderson S. A. 1998b. Modelling of shearing behaviour of a residual soil with recurrent neural network. Int. J. Numerical and Analytical Methods in Geomechanics.