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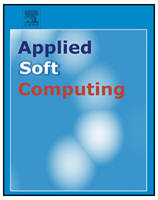

Lateral load bearing capacity modelling of piles in cohesive soils in undrained conditions: An intelligent evolutionary approach

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ABSTRACT

The complex behaviour of fine-grained materials in relation with structural elements has received noticeable attention from geotechnical engineers and designers in recent decades. In this research work an evolutionary approach is presented to create a structured polynomial model for predicting the undrained lateral load bearing capacity of piles. The proposed evolutionary polynomial regression (EPR) technique is an evolutionary data mining methodology that generates a transparent and structured representation of the behaviour of a system directly from raw data. It can operate on large quantities of data in order to capture nonlinear and complex relationships between contributing variables. The developed model allows the user to gain a clear insight into the behaviour of the system. Field measurement data from literature was used to develop the proposed EPR model. Comparison of the proposed model predictions with the results from two empirical models currently being implemented in design works, a neural network-based model from literature and also the field data shows that the EPR model is capable of capturing, predicting and generalizing predictions to unseen data cases, for lateral load bearing capacity of piles with very high accuracy. A sensitivity analysis was conducted to evaluate the effect of individual contributing parameters and their contribution to the predictions made by the proposed model. The merits and advantages of the proposed methodology are also discussed.

1. Introduction

Deep foundations are used as an effective way of avoiding lower quality soils or transferring large loads to the soil lying underneath the structures. Analysis and design of deep foundations under various loading conditions is widely investigated by researchers in the past few decades. Some research contributions have revealed that solving equations of static equilibrium can be an effective way of designing axially loaded piles, whereas, design of laterally loaded piles will only be possible by solving nonlinear differential equations. Poulos and Davis [1] implemented a methodology based on elasticity, by adopting a previously developed soil model, to analyze the behaviour of piles. However, their proposed approach was not suitable for the nonlinear analysis of behaviour of soil and pile systems. The analysis of nonlinear soil behaviour has been conducted by Matlock and Reese [2] and Portugal and Seco e Pinto [3]. Portugal and Seco e Pinto [3] also utilized the finite element method for numerically predicting the behaviour of laterally loaded piles. This methodology is widely used in analysis and design of deep foundations despite the presence of uncertainties in such predictions due to the variability of soil properties. Semi-empirical methods were also suggested for analysis and design of laterally loaded piles and for predicting their load bearing capacity (e.g. [4]).

In recent years, artificial neural network (ANN) models have been proposed as alternates to experimental and empirical approaches [5–7]. Goh [8] used a back propagation neural network (BPNN) to predict the skin friction of piles in clayey soils. Goh [9,10] showed that artificial neural network models outperform some of the existing empirical models in predicting the ultimate load bearing capacity of timber piles in clay and pre-cast concrete and also steel piles in cohesionless soils. Chan et al. [11] and Teh et al. [12] argues that artificial neural networks have been successful in predicting the static load bearing capacity of piles and their predations are in agreement with the outcomes of analyses conducted using commercial software CAPWAP [13]. Lee and Lee [14] utilized neural networks to predict the ultimate bearing capacity of piles based on data simulated using previously suggested models and also in situ pile loading test results. Abu-Kiefa [15] used a probabilistic neural network model, generalized regression neural network (GRNN), to predict the pile load bearing capacity considering the contributions of the tip and shaft separately and also the total load bearing capacity of piles driven into cohesionless soils. Nawari et al. [16] used neural networks for predicting the axial load bearing capacity of steel piles (including the ones with H cross sectional shape) and also pre-stressed and reinforced concrete piles using both back propagation and generalized regression neural networks. The same authors also predicted the settlement of the top of the drill shaft due to lateral loading of piles with similar methodology based on data from in situ tests.

Artificial neural networks have mostly been used to predict the vertical load bearing capacity of piles and their performance is usually measured based on the

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coefficient of correlation (*R*). Coefficient of correlation is commonly used amongst researchers; however, it is difficult to judge, based on this method, whether the developed model is over-predicting or under-predicting the actual values. As a result, Briaud and Tucker [17] have strongly emphasized that other statistical criteria should also be implemented along with the coefficient of correlation to evaluate the quality of the predictions of the ANN models created for pile load bearing capacity. To address this issue, Abu-Farsakh [18] used statistical parameters, mean and standard deviation, calculated for the ratio of predicted pile capacity (Q_p) over the measured pile capacity (Q_m) to evaluate the quality of the predictions of the model. Das and Basudhar [19] also suggested an artificial neural network model for predicting lateral load capacity of piles and used similar procedures suggested by Abu-Farsakh [18] to evaluate their presented model.

The results of previous works have shown that artificial neural network offers great capabilities and advantages in modelling the behaviour of materials and systems. However, it is generally accepted that ANNs also suffer from a number of shortcomings. One of the main shortcomings of the neural network based approach is that the optimum structure of the neural network (e.g. the number of input layers, hidden layers and transfer functions) needs to be identified a priori through a time consuming trial and error procedure. Another main drawback of the neural network approach is the large complexity of the structure of ANN. This is because the neural network stores and represents the knowledge in the form of weights and biases which are not easily accessible to the user. Artificial neural networks are considered as black-box systems as they are unable to explain the underlying principles of prediction and the effect of inputs on the output [20].

A number of investigators have studied the use of connection weights to interpret the contributions of input variables to neural network models [21–23]. However, interpretation of weights may still be considered a subject of further research in the future.

In this paper an evolutionary-based data mining approach is proposed to model the bearing capacity of laterally loaded piles in undrained conditions. The evolutionary polynomial regression has been successfully applied to modelling a number of civil engineering materials and systems including torsional strength prediction for reinforced concrete beams [24], stress–strain and volume change behaviour of unsaturated soils [25], stability of soil and rock slopes [26], mechanical behaviour of rubber concrete [27] and permeability and compaction characteristics of soil [28]. EPR provides a structured and transparent representation of the model in the form of mathematical (polynomial) expressions to describe the complicated behaviour of systems. The proposed methodology overcomes most of the issues and drawbacks associated with the neural network modelling approach by providing clear insight into the behaviour of the system and the levels of contribution of the influencing parameters in the developed models.

2. Database

Field measurement data from literature is used to develop and evaluate the proposed EPR model. From among 38 data cases [29], 29 cases, representing 80% of the total data, were used to train the EPR model and the remaining cases were kept unseen to EPR during the model development process and were used in the model evaluation stage to examine generalization capabilities of the created model.

Tables 1 and 2 represent the training and testing data sets used in EPR model development and validation stages respectively. The

Table 1
Field measurement data for lateral load capacity of piles and contributing parameters (training data set).

Diameter, *D* (mm)	Embedded length, *L* (mm)	Eccentricity, *e* (mm)	Undrained shear strength, S_u (kN/m^2)	Lateral load bearing capacity, Q_m (N)
6.35	146.1	19.1	38.8	69.5
13	260	0	24	225
12.5	130	0	24	106
13.5	300	50	3.4	30
13.5	300	50	4	36
13.5	300	50	5.5	50
13.5	300	50	7.2	64
18	300	50	10	89
18	300	50	3.4	3
20.4	300	50	4	46
12.3	300	50	5.5	44
18.4	300	50	4	51
18	300	50	10	116.5
33.3	300	50	3.4	78.5
33.3	300	50	5.5	110.5
12.3	300	50	3.4	29.5
6.35	139.7	25.4	38.8	65.5
12.3	300	50	7.2	58
12.3	300	50	10	81
18.4	300	50	5.5	65.5
18.4	300	50	7.2	86.5
18.4	300	50	10	114
20.4	300	50	5.5	59.5
20.4	300	50	7.2	76.5
20.4	300	50	10	87
25.4	300	50	7.2	90
25.4	300	50	10	151.6
25.4	300	50	3.4	50
25.4	300	50	5.5	75

Table 2
Field measurement data for lateral load capacity of piles and contributing parameters (validation data set).

Diameter, *D* (mm)	Embedded length, *L* (mm)	Eccentricity, *e* (mm)	Undrained shear strength, S_u (kN/m^2)	Lateral load bearing capacity, Q_m (N)
13.5	190	0	24	128
20.4	300	50	3.4	38
18.4	300	50	3.4	42.5
25.4	300	50	4	58
13	132	33.8	38.8	53
18	300	50	4	49
18	300	50	5.5	65
18	300	50	7.2	87
12.3	300	50	4	35

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