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Evolutionary computing to determine the skin friction capacity of piles embedded in clay and evaluation of the available analytical methods

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Evolutionary computing to determine the skin friction capacity
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22 Abstract

Deep foundations are very important elements in the routine design of railways and 23 24 bridges when the loads applied due to these important structures are higher than the bearing capacity of the soil. However, the methods currently available to calculate the 25 bearing capacity of driven piles embedded in clay have been developed based on 26 empirical factors derived from limited tests. Hence, further assessment of these 27 methods and the development of new methods are urgently required. This paper 28 discusses the development of a new robust model to calculate the skin friction capacity 29 30 of driven piles using the multi-objective evolutionary polynomial regression (MOGA-EPR) analysis. The paper also evaluates the accuracy of the available analytical 31 32 methods. Real field results of skin friction capacity of driven piles have been used to achieve the objectives of the study. The results showed that the MOGA-EPR predicts 33 the skin friction of driven piles with an excellent accuracy and better than the available 34 analytical methods, with a mean absolute error (MAE), a root mean square error 35 (*RMSE*), mean (μ), a standard deviation (σ), a coefficient of determination (R^2), the 36 variance account for (VAF) and a20 - index of 3.4, 4.6, 1.03, 0.24, 0.98, 99, and 0.75, 37 respectively, for the training data, and 4.2, 5.3, 1.12, 0.15, 0.91, 97 and 0.77, 38 39 respectively, for testing data. In addition, a novel model to predict the skin friction capacity of driven piles has been proposed based on the MOGA-EPR analysis and 40 this model can be used by engineers and researcher with confidence. The evaluation 41 of the analytical methods illustrated that the Lambda method accuracy is better than 42 the Alpha and Beta methods as this method scored a less mean error (MAE = 7.8 and 43 RMSE = 12.5), a less standard deviation (σ = 0.21), a higher coefficient of 44 determination ($R^2 = 0.91$), higher value for the variance account for (VAF=89) 45 compared with the other analytical methods. In addition, the Beta method scored 46 lowest compared with the other analytical methods with MAE, RMSE, μ , σ , R^2 , VAF 47 and a20 - index of 17.2, 28.0, 1.07, 1.00, 0.55, 40 and 0.37, respectively. The findings 48 of this study will help to achieve robust calculations of pile capacity and reduce 49 uncertainty associated with the choice of the analytical method used in the design of 50 driven piles in clay. 51

Keywords: Evolutionary polynomial regression analysis; skin friction; driven piles;
 analytical methods

Highlights:

- A novel mathematical model has been proposed to predict the skin friction capacity of driven piles embedded in clay.
- The Lambda method produced the lowest error and highest coefficient of determination compared with the other analytical methods.
- The Beta method scored lowest in the assessment of the current analytical methods.

75 **1. Introduction**

Deep foundations are very important elements in the design of offshore structures, 76 77 high-rise buildings, railways and bridges when the loads applied due to these important structures are higher than the bearing capacity of the soil (Li et al., 2019). 78 79 The urgent demand for the expansion of such heavy structures has been the main reason for more reliable and robust design methods to accurately predict the bearing 80 capacity of deep foundations as this is the main factor controlling the design of deep 81 foundations (Doherty and Gavin, 2011; Alkroosh et al., 2015). The main issue is that 82 83 the design methods used to predict the bearing capacity of deep foundations have been developed based on factors derived from limited tests (Doherty and Gavin, 84 85 2011). Therefore, the accuracy of these design methods requires further assessment and testing. In addition, and due to the complexity of the pile behaviour and the limited 86 tests used to develop the design methods, many previous studies have attempted to 87 use data driven methods to predict the bearing capacity and settlement of deep 88 foundations (Singh and Walia, 2017; Shahin, 2016). These previous studies are 89 summarized in Table 1, the summary includes the data driven method/s each study 90 considered, the input parameters, the output of the data driven method/s and the 91 92 number of data points used.

93 In addition to Table 1, there are several studies that have been conducted on the skin friction capacity of piles due to the importance of skin friction in practice as most of the 94 95 piles are designed to allow very small settlement. The acceptance of a very small settlement in practice means that the routine design of these piles is based on the skin 96 97 friction, as the end bearing capacity requires a settlement equal to or more than 10% of the diameter of the pile and such settlement is not acceptable in practice. Most of 98 the past studies on the skin friction capacity have focused on the use of data driven 99 methods to predict pile capacity, while there is very limited work concerned with the 100 evaluation of the accuracy of the current analytical methods. 101

Goh (1995) used artificial neural networks (ANN) to predict the skin friction capacity of driven piles embedded in clay and found that the ANN achieved good prediction of the skin friction, where the coefficient of correlation (R) ranged between 0.86 to 0.99 for the training data (the data used in the development of the ANN model) and 0.94 to 0.96 for the testing data. Goh (1995) also found that ANN predicted the skin friction 107 capacity with an accuracy better than the Alpha and Beta methods (Alpha and Beta 108 methods are analytical methods developed to predict the skin friction capacity of pile 109 embedded in cohesive soils and will be discussed in the next section), where the R for 110 the Alpha and Beta methods was equal to 0.98 and 0.73 for the training data, and 0.89 111 and 0.70 for the testing data. Cherubini and Vessia (2007) evaluated the accuracy of 112 the Alpha method in predicting the skin friction capacity of bored piles embedded in 113 clay.

Samui (2008, 2011) and Prayogo (2018) used a support vector machine (SVM) 114 115 approach to predict the skin friction capacity of piles embedded in clay and also found that SVM provided good prediction of the skin friction capacity as the SVM produced 116 117 low root mean square error values (which ranged between 4.4 to 13.9), low mean absolute error values (which ranged between 3.2 to 9.4), and high R values (which 118 ranged between 0.93 to 0.99). Suman et al. (2016) tested the capabilities of 119 multivariate adaptive regression splines (MARS) and functional networks (FN) to 120 predict the skin friction of driven piles embedded in clay. Suman et al. (2016) found 121 that these methods predicted the skin friction capacity with an accuracy better than 122 the ANN, SVM, Alpha and Beta methods, as these methods scored lower mean 123 absolute error values and lower root mean square error values. 124

125 Moayedi and Hayati (2018b) developed design charts and a mathematical model to predict the skin friction capacity of driven piles embedded in clay. The design chart 126 127 was developed based on ANN and the mathematical model was developed based on genetic programing (GP). Samui (2019) used Gaussian Process Regression (GPR) 128 129 and Minimax Probability Machine Regression (MPMR) to predict the skin friction of driven piles embedded in clay and found that these methods estimated the skin friction 130 capacity better than the ANN. The calculated mean absolute error was equal to 3.2, 131 2.0 and 2.0 for the ANN, GPR and MPMR, respectively. In addition, the calculated 132 mean root square error for the aforementioned methods was equal to 5.3, 4 and 4, 133 respectively. 134

Based on the literature review it is clear that many attempts have been made to predict the skin friction capacity of piles embedded in clay using data driven techniques, i.e. using ANN, SVM, MARS, FN, GP, GPR and MPMR. However, ANN is a black box method as it does not give the relationship between the dependent and the

independent variables (Faramarzi, 2011); hence, such a technique does not clearly 139 show the influence of the pile length, pile diameter, undrained shear strength and 140 effective stress on the skin friction capacity. Furthermore, SVM, MARS, FN, GP, GPR 141 and MPMR provide complicated models, which cannot be easily interpreted and used. 142 Also, no study in the literature has evaluated the capabilities of multi-objective 143 evolutionary polynomial regression analysis (MOGA-EPR) in predicting the skin 144 friction capacity of piles, although this method provides robust and simple 145 mathematical models as demonstrated in many studies in the literature (Ahangar-Asr 146 147 et al., 2014, 2016, 2018; Fiore et al., 2016; Alzabeebee et al., 2018, 2019; Alzabeebee, 2019, 2020). In addition, previous studies evaluated the accuracy of Alpha method in 148 predicting the skin friction capacity of bored piles (Cherubini and Vessia, 2007), and 149 Alpha and Beta methods for the case of driven piles (Goh, 1995; Suman et al., 2016). 150 However, Goh (1995) and Suman et al. (2016) did not mention the method used to 151 152 calculate the α parameter (which is a factor used in the Alpha method to calculate the skin friction capacity of piles embedded in clay) for the case of driven piles, although 153 more than one approach is available in the literature to calculate the α parameter as 154 will be discussed in the next section. In addition, the previous studies did not evaluate 155 the accuracy of the Lambda method, which is also an analytical method to predict the 156 157 skin friction capacity of piles embedded in clay. Therefore, this study aims to improve the state-of-the-art with respect to the prediction of the skin friction of driven piles by 158 considering two important objectives: 159

1- The first objective is to use a very powerful and new data driven method to 160 predict the skin friction capacity of driven piles in clay; the method is the multi-161 objective evolutionary polynomial regression analysis. The strength of this 162 method over the traditional data driven methods is that it has the ability to 163 provide robust and simpler prediction models (Faramarzi, 2011) as the EPR 164 gives the relationship between the parameters in the form of a simple 165 mathematical expression (Ahangar-Asr et al., 2014, 2016, 2018; Alzabeebee 166 et al., 2018, 2019; Nassr et al., 2018a, b). Having an equation as an outcome 167 of the analysis is required to aid future designs and to make it easy to test this 168 equation further when new data becomes available. 169

2- The second objective is to assess the current analytical methods which have
 been developed to predict the skin friction capacity of bored piles embedded in

- 172 clay and understand the limitations and the capabilities of these methods, and 173 to compare the prediction capabilities of these methods with the predictions
- 174 from the multi-objective evolutionary polynomial regression analysis.
- 175 The methodology of this research is briefly summarized in Figure 1. More details on 176 the methodology will be discussed in Sections 2, 3, 4 and 5.
- 177 Table 1: Summary of previous studies which have used data driven methods to predict
- 178 pile settlement and capacity

Reference	Data driven method used	Input parameters	Output of the data driven method	Number of load tests
Shahin (2010)	ANN	D_{eq} , L, D_{stem} , D_{base} , $q_{c_{tip}}$, $q_{c_{shaft}}$ and Fs	Qu	80 load tests for driven piles and 94 load tests for bored piles
Alkroosh and Nikraz (2011a)	GEP	$D, L, q_{c_{tip}},$ $q_{c_{shaft}}$ and Fs	Qu	50 load tests for bored piles and 28 load tests for driven pile
Alkroosh and Nikraz (2011b)	ANN	$D, L, q_{c_{tip}},$ $q_{c_{shaft}}, \Delta(\frac{S}{D}),$ $P_i \text{ and } P_{i+1}$	S/D	50 load tests for bored piles and 30 load tests for driven pile
Ismail and Jeng (2011)	ANN	D, L, P_i, E and k_s	S/D	98
Alkroosh and Nikraz (2012)	GEP	D_{eq} , L, $q_{c_{tip}}$, Fs, $q_{c_{shaft}}$ and E	Qu	25

Alkroosh and Nikraz (2014)	GEP	$D, L, N_{shaft},$ N_{tip}, St and HE	Qu	25
Momeni et al. (2014)	ANN enhanced with genetic algorithm (GA) optimization technique	L, A, St, W, and H	Qu	50
Shahin (2014a)	RNN	$D, L, q_{c_{tip}}, Fs,$ f_{R-tip} and $f_{R-shaft}$	S/D	38
Shahin (2014b)	RNN	$D, L, q_{c_{tip}}, Fs,$ f_{R-tip} and $f_{R-shaft}$	S/D	23
Milad et al. (2015)	ANN and GEP	$c'_{avg}, \phi'_{avg}, \delta,$ γ', FPN, L and A	Qu	100
Momeni et al. (2015)	ANN	$L, St, A, N_{shaft},$ and N_{tip}	fs, Qp and Qu	36
Armaghani et al. (2017)	ANN and hybrid PSO- ANN	Ls/Lr, D , L , UCS and N_{av}	Qu	132
Nejad and Jaksa (2017)	ANN	Type of pile test, type of pile, type of installation, <i>L</i> , <i>A</i> , <i>E</i> , <i>O</i> , $q_{c_{tip}}$, $q_{c_{shaft}}$, <i>Fs</i> and P_i	S/D	56
Harandizadeh et al. (2018a)	ANFIS	$L, D, q_{c_{tip}}$ and Fs	Qu	72

Harandizadeh et al. (2018b)	RBFNN, BR, LM and MT	$c'_{avg}, \phi'_{avg}, \delta,$ γ', FPN, L and A	Qu	100
Moayedi and Hayati (2018a)	FFNNs and FTDNNs	$D, L, q_{c_{tip}}$ and $q_{c_{shaft}}$	S/D	50
Moayedi and Armaghani (2018)	ANN optimised with imperialism competitive algorithm	$arphi_{shaft}^{\prime}, \qquad arphi_{tip}^{\prime}, \ \sigma_{tip}^{\prime}, \ L \ ext{and} \ A$	Qu	59
Shaik et al. (2018)	ANN optimised with imperialism competitive algorithm and neuro-fuzzy inference system	$ec{ extsf{w}}_{shaft}^{\prime}, ec{ extsf{w}}_{tip}^{\prime}, \ \sigma_{tip}^{\prime}, L extsf{and} A$	Qu	59
Chen et al. (2019)	neuro-genetic, neuro- imperialism, GEP and ANN	<i>L</i> , <i>A</i> , <i>St</i> , <i>W</i> , and <i>H</i>	Qu	50
Harandizadeh et al. (2019)	ANFIS– GMDH–PSO and FPNN– GMDH	L, D, q _{ctip} and Fs	fs and Qu	72

179 Note: ANN: artificial neural networks, D_{eq} : driven pile shaft equivalent diameter, *L*: 180 length of the pile, D_{stem} : bored pile stem diameter, D_{base} : bored pile base diameter, 181 $q_{c_{tip}}$: weighted average cone point resistance over pile tip failure zone, q_{shaft} : 182 weighted average cone point resistance along pile shaft, *Fs*: weighted average cone 183 sleeve friction resistance, *Qu*: ultimate pile capacity, GEP: Gene expression 184 programming, *D*: diameter of the pile, $\Delta(\frac{S}{D})$: normalized settlement increment, P_i :

current load state, P_{i+1} : future load state, S/D: pile settlement to pile diameter, E: 185 modulus of elasticity of the pile, k_s : soil stiffness, , N_{shaft} : average number of blows of 186 the standard penetration test along the pile shaft, N_{tip} : number of blows of the standard 187 penetration test at the pile tip, St: pile set, HE: hammer energy, A: cross-section area 188 of the pile, W: hammer weight, H: hammer drop height, RNN: recurrent neural 189 networks, f_{R-tip} : friction ratio at the pile tip, $f_{R-shaft}$: friction ratio along the pile shaft, 190 c'_{avg} : average effective cohesions of the soil along the pile shaft, ϕ'_{avg} : average angle 191 of shearing resistance along the pile shaft and pile tip, δ : pile-soil friction angle, γ' : 192 effective unit weight of the soil, FPN: flap number, fs: skin friction capacity of the pile, 193 Qp: end bearing capacity of the pile, PSO-ANN: artificial numeral network enhanced 194 195 with particle swarm optimization, Ls/Lr: length of soil layer to socket length, UCS: uniaxial compressive strength, N_{av} : average number of blows based on the standard 196 penetration test the pile shaft and pile tip, 0: perimeter of the pile in contact with the 197 soil, ANFIS: neuro-fuzzy inference system, RBFNN: radial basis function neural 198 network, BR: feedforward Bayesian regulation learning algorithm, LM: feedforward 199 Levenberg-Marguardt algorithm, MT: model tree algorithm, FFNNs: feed-forward 200 neural networks, FTDNNs: focused time-delay neural networks, p'_{shaft} : average 201 shearing resistance along the pile shaft, ϕ'_{tip} : average shearing resistance at the pile 202 tip, σ'_{tip} : effective stress at the pile tip, ANFIS-GMDH-PSO: neuro-fuzzy inference 203 system and group method of data handling structure optimized by particle swarm 204 optimization algorithm, FPNN-GMDH: fuzzy polynomial neural network type group 205 method of data handling 206

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228 Figure 1: Flow chart of the methodology of this research

229 2. Current analytical methods

There are currently three analytical methods available in the literature to estimate the skin friction capacity of driven piles embedded in clay (Das, 2011). These methods are:

233 1- Lambda (λ) method:

This method was proposed by Vijayvergiya and Focht (1972) and is based on the idea that the pile driving into the soil induces passive lateral earth pressure (Das, 2011). The method includes the vertical effective stress (σ'_{ave}) and proposes that the skin friction (*fs*) of the driven pile can be calculated using Equation 1. The λ factor in Equation 1 depends on the embedment depth of the pile (*L*) as shown in Figure 2.

$$fs = \lambda(\sigma'_{ave} + 2S_u) \tag{1}$$

Where, σ'_{ave} is the average vertical effective stress and S_u is the undrained shear strength.



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244 2- Alpha (α) method:

This method proposes that the skin friction of a driven pile is a percentage of the undrained shear strength by using an empirical adhesion factor called α as shown in Equation 2. This α empirical factor was originally proposed by Tomlinson in 1957 (Terzaghi, 1996). However, there are three methods currently available to estimate the α factor. These methods can be summarized as follows:

- Sladen (1992) method:

Figure 2: Relationship between the λ factor and the embedment depth of the pile (data is from Das (2011))

Sladen (1992) proposed Equation 3 to predict the α coefficient. The *C* factor in

Equation 3 is equal to or greater than 0.5 for driven piles (Das, 2011).

253 - ISO (2016) method:

ISO (2016) suggested two different equations to calculate the α factor depending on the ratio of the undrained shear strength to the average vertical effective stress as shown in Equations 4 and 5.

- Terzaghi et al. (1996) method:

Terzaghi et al. (1996) suggested predicting the α coefficient from Figure 3; *Pa* in Figure 3 is the atmospheric pressure (100 kPa). This Figure has been developed based on data collected from Dennis and Olson (1983) and Stas and Kulhawy (1984). However, Terzaghi et al. (1996) also recommended multiplying the α coefficient obtained from Figure 3 by 0.54 (i.e. a reduction factor) for piles with a length equal to or greater than 50 m. Also, for pile lengths from 30 m to 50 m, the reduction factor varies linearly between 1.00 and 0.56.

$$fs = \alpha S_u \tag{2}$$

$$\alpha = C \left(\frac{\sigma_{ave}}{S_u}\right)^{0.45} \tag{3}$$

$$\alpha = 0.5 \left(\frac{S_u}{\sigma'_{ave}}\right)^{-0.5} \quad \text{for } \frac{S_u}{\sigma'_{ave}} \le 1 \tag{4}$$

$$\alpha = 0.5 \left(\frac{S_u}{\sigma'_{ave}}\right)^{-0.25} \text{ for } \frac{S_u}{\sigma'_{ave}} > 1 \tag{5}$$



Figure 3: The α factor based on Terzaghi et al. (1996)

267 3- Beta (β) method

This method considers a different approach compared to the other two methods. In this method, the skin friction is determined using the drained angle of internal friction of the remolded clay (ϕ') as shown in Equations 6 to 9 (Das, 2011). The beta factor ranges between 0.25 to 0.4 (Goh, 1995).

$fs = \beta \sigma'_{ave}$	(6)
$\beta = K \tan \phi'$	(7)
$K = 1 - \sin \phi'$ for normally consolidated clay	(8)
$K = (1 - \sin \phi') \sqrt{OCR}$ for over consolidated clay	(9)

272 Where, *OCR* is the over-consolidation ratio.

3. Data used in the analyses

The data used in the current study have been adapted from a database of skin friction 274 capacities of driven piles presented by Goh (1995). The database comprises 65 points 275 of data on the skin friction capacity of driven piles (fs). In addition, the data contains 276 the length of the pile (L), the diameter of the pile (D), the average vertical effective 277 278 stress (σ'_{ave}) and the average undrained shear strength (S_{u}). Goh (1995) developed this database by collecting results from the literature; these results were for pile load 279 tests conducted on timber and steel pipe piles. It is worth mentioning that these 280 parameters have been selected as they are the most influential parameters with 281 respect to the skin friction capacity of the pile. These parameters have also been used 282 in previous studies for the prediction of the skin friction capacity of piles (Goh, 1995, 283 Samui, 2008, 2011, 2019, Suman et al., 2016, Prayogo, 2018, Moayedi and Hayati, 284 2018b). 285

Table 2 shows the mean, standard deviation, maximum value (Max.), minimum value (Min.) and range of the collected data.

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Statistic	Parameter				
indicator	<i>L</i> (m)	<i>D</i> (cm)	σ_{ave}' (kPa)	S_u (kPa)	fs (kPa)
Mean	21.55	31.45	124.58	62.16	40.85
Standard	16.37	16.61	127.71	60.03	36.52
deviation					
Max.	96.00	76.70	718.00	335.00	192.10
Min.	4.60	11.40	19.00	9.00	8.00
Range	91.40	65.30	699.00	326.00	184.10

Table 2: Statistics of the data used in this study

4. Multi-objective evolutionary polynomial regressions analysis (EPR)

Multi-Objective Evolutionary Polynomial Regression (MOGA-EPR) is a genetic 292 algorithm-based regression analysis developed by Giustolisi and Savic (2009) based 293 294 on the original evolutionary polynomial regression analysis developed by Giustolisi and Savic (2006). The methodology of MOGA-EPR is based on using a genetic 295 296 algorithm in combination with a regression analysis (Alzabeebee et al., 2018, 2019; Alzabeebee, 2019, 2020). In this method, the 'fitting' is conducted utilizing the least 297 298 square method and the selection of the best fitting model is done using the genetic 299 algorithm. The MOGA-EPR controls the model fitness and model complexity using spread functions to enable more robust analyses (Giustolisi and Savic, 2009). This 300 method also controls overfitting issues by using penalization procedures. 301

Equation 10 presents the starting point of the MOGA-EPR (Giustolisi and Savic, 2006).
This equation produces an over-determined system, which is solved based on the
least square methodology (Giustolisi and Savic, 2006).

$$y = \sum_{j=1}^{m} F(X, f(X), a_j) + a_0$$
(10)

Where *y* is the estimated output skin friction, a_j is a constant value, *F* is an assumed governing function between the input and the output variables; this function develops as the analysis time increases and based on artificial intelligence. X represents the independent variables matrix, *f* is the general form of the output function and *m* is the maximum number of terms in the produced equation and it is set by the user, and a_0 is the bias.

After solving Equation 10, the MOGA-EPR is formulated to find the model, which 311 provides the best fit to the data by using different combinations of the exponents with 312 the aid of artificial intelligence. Finally, the performance of the developed model is 313 judged by determining a coefficient called the coefficient of determination (CD) and the 314 model which scores the highest *CD* is selected; the *CD* is determined using Equation 315 11 (Alani et al., 2014a, b; Faramarzi et al., 2014). It is worth noting that the exponents 316 considered in the EPR analysis are also controlled by the user. More information on 317 the MOGA-EPR can be found in Alani et al. (2014); Faramarzi et al. (2014); Ahangar-318 Asr et al. (2014) and Alzabeebee (2017). 319

$$CD = 1 - \frac{\sum_{N} (fs_{(m)} - fs_{(p)})^{2}}{\sum_{N} (fs_{(m)} - \frac{1}{N} \sum_{N} fs_{(p)})^{2}}$$
(11)

Where, $fs_{(m)}$ is the measured skin friction, $fs_{(p)}$ is the predicted skin friction, and *N* is the number of the input data used in the development of the model.

5. Criteria considered to evaluate the accuracy of the MOGA-EPR model and the analytical methods

The quality of the prediction of the MOGA-EPR model and the available analytical methods have been assessed following a statistical based methodology similar to previous studies (Ozer et al., 2008; Alkroosh et al., 2014, 2015; Onyejekwe et al., 2015; Huang et al., 2019). The following points summarize the statistical measures used in the evaluation methodology:

The first statistical measure was based on finding the error in the prediction by
calculating the mean absolute error (MAE) and the root mean square error
(RMSE). Equations 12 and 13 show the mathematical formulation of the MAE
and the RMSE (Ozer et al., 2008; Onyejekwe et al., 2015; Huang et al., 2019).
The lower the MAE and the RMSE, the better the prediction. It is worth
mentioning that the MAE has been considered because it provides insight into
the average error of the prediction. In addition, the RMSE has been considered

because it provides useful insight into the large error of the prediction, as the errors are squared before they are averaged as can be clearly noted in Equation 13 (Ashtiani et al., 2018).

$$MAE = \frac{1}{n} \sum_{1}^{n} |fs_{(p)} - fs_{(m)}|$$
(12)

$$RMSE = \sqrt{\frac{1}{n} \sum_{1}^{n} (fs_{(p)} - fs_{(m)})^{2}}$$
(13)

Where, *n* is the number of data points used in the evaluation; $fs_{(p)}$ is the predicted skin friction of the pile; and $fs_{(m)}$: is the skin friction measured in the field.

2- The second statistical measure was based on calculating the mean (μ) of the ratio of the predicted skin friction to the measured skin friction as shown in Equation 14 (Onyejekwe et al., 2015). The expected range of the mean is zero to infinity. However, the optimum prediction should score a mean equal to 1 (Onyejekwe et al., 2015). The predictive model underestimates the skin friction if the mean is less than one and overestimates the skin friction if the mean is higher than one.

$$\mu = \frac{1}{n} \sum_{1}^{n} \left(\frac{fs_{(p)}}{fs_{(m)}} \right)$$
(14)

3- The third statistical measure was the standard deviation (σ) of the predicted 348 skin friction to the measured skin friction. The standard deviation is calculated 349 using Equation 15. The standard deviation provides a good indication to the 350 distribution of the predicted values around the mean. The range of the standard 351 deviation is between zero and one. A zero value provides the optimum 352 prediction in which the scatter of the prediction around the mean a minimum. 353 However, a value of one means a maximum scatter around the mean. Hence, 354 the closer the standard deviation is to zero, the better the prediction (Alkroosh 355 and Nikraz, 2014). 356

$$\sigma = \sqrt{\frac{\sum_{1}^{n} \left(\frac{fs_{(p)}}{fs_{(m)}} - \mu\right)^{2}}{n - 1}}$$
(15)

4- The fourth statistical measure was the coefficient of determination (R^2) . The R^2 measures the average error of the prediction. The R^2 ranges between zero and one, with an optimum value of one. Hence, the closer R^2 is to one, the better the prediction accuracy (Alzabeebee et al. 2017; Tinoco et al. 2019). R^2 is calculated using Equation 16 (Mohammadzadeh et al., 2019).

$$R^{2} = \frac{\sum_{i=1}^{n} (fs_{(p)_{i}} - fs_{(p)_{average}})(fs_{(m)_{i}} - fs_{(m)_{average}})}{\sqrt{\sum_{i=1}^{n} (fs_{(p)_{i}} - fs_{(p)_{average}})^{2} \sum_{i=1}^{n} (fs_{(m)_{i}} - fs_{(m)_{average}})^{2}}}$$
(16)

Where, $fs_{(p)_{average}}$ is the average of the predicted skin friction values and $fs_{(m)_{average}}$ is the average of the measured skin friction values.

5- The fifth statistical measure was the variance account for (*VAF*). The *VAF* is usually employed to check the correctness of the predictive model. This is done by comparing the measured and the predicted output using Equation 17 (Armaghani et al., 2017). A *VAF* value of 100 means that the predictive model provides a perfect estimation of the output. Therefore, the closer the *VAF* of the predictive model to 100, the better the prediction (i.e. lower variance).

$$VAF = \left[1 - \frac{var(fs_{(m)} - fs_{(p)})}{var(fs_{(m)})}\right] \times 100$$
(17)

6- The final statistical measure was the a20 - index. This statistical measure evaluates the percentage of the predictive outputs that falls within the range of 80% to 120% of the measured output. A value of the a20 - index of 1.0 means that the predictions of the models are equal to, or below, a 20% error. In addition, the closer the a20 - index is to 1 the better, as it means that there are many predictions that are equal to, or below, a 20% error. The a20 - index is calculated using Equation 18 (Armaghani, 2020).

$$a20 - index = \frac{m20}{n} \tag{18}$$

Where, m20 is the number of results where the predicted to the measured skin friction is between 0.8 to 1.2.

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6. Development of the MOGA-EPR model

380 The data, with statistics shown in Table 2, has been used to develop the MOGA-EPR model. This data has been divided into two groups: training data and testing data. 80% 381 382 of the data has been used in the model development (training stage) and 20% of the data has been used in the model testing and validation (testing stage). It should be 383 noted that dividing the data into training and test data is common in the development 384 of data driven models, i.e. the training data is used in the training and the development 385 of the MOGA-EPR model, and the performance of the developed model has been 386 checked using independent data that has not been used in the training stage. Hence, 387 the use of testing data ensures the robustness and accuracy of the developed model 388 (Alani et al., 2014a, b; Faramarzi et al., 2014; Ahangar-Asr et al., 2014; Alzabeebee, 389 2017, 2019, 2020; Alzabeebee et al., 2018, 2019). However, to avoid model 390 extrapolation the variables of the testing data should be in the range of the data used 391 in the model training (i.e. model development) (Alzabeebee, 2017, 2019, 2020; 392 Alzabeebee et al., 2018, 2019). Hence, the data have been randomly shuffled and 393 divided into two group, then statistical analyses have been conducted to ensure that 394 395 the training and testing data are consistent. Tables 3 and 4 show the mean, standard deviation, maximum value (Max.), minimum value (Min.) and the range of both the 396 397 training and testing data, respectively. The tables demonstrate the consistency of the training and the validation data. 398

The MOGA-EPR analysis was conducted after ensuring that the data are consistent. Several structures and exponents of the mathematical model are now examined, and the performance of the obtained model is also studied using the criteria discussed previously in this paper. Equation 18 shows the best mathematical model obtained from the MOGA-EPR analysis. Figures 4a, b, c, d, e, f and g show the obtained *MAE*, *RMSE*, μ , σ , R^2 , *VAF* and a20 - index values for the training and testing data, respectively. Figure 4a clearly shows that the developed MOGA-EPR model gives a

very good accuracy with a MAE of 3.4 and 4.2 for the training and testing data, 406 respectively. The obtained *RMSE* results presented in Figure 4b also show that the 407 model offers a very good prediction, where the *RMSE* is equal to 4.6 and 5.3 for the 408 training and testing data, respectively. The μ values shown in Figure 4c give additional 409 proof of the accuracy, where the developed model slightly overestimates the skin 410 friction as the obtained μ values are 1.03 and 1.12 for the training and testing data, 411 respectively. Furthermore, the obtained values of the σ (Figure 4d) and R^2 (Figure 4e) 412 also show the strength of the model, where σ is equal to 0.24 for the training and 0.15 413 for the testing data and R^2 is very close to one being equal to 0.98 and 0.91 for the 414 training and the testing data, respectively. The results of the VAF (Figure 4f) provides 415 additional trust in the robustness of the model as the obtained VAF is very close to 416 417 100 for training and testing data (99 for training data and 97 for testing data). The a20 - index analyses (Figure 4g) also demonstrate the prediction capabilities of the 418 models as the percentage of the obtained predictions with error less than or equal to 419 420 20% is 75% and 77% for training and testing data, respectively.

$$fs = 28.44 \frac{D \cdot \sqrt{S_u}}{L^3} - 3 \times 10^{-7} \frac{\sqrt{D} \cdot \sqrt{\sigma'_{ave}} \cdot S_u^3}{L^2} - 83.81 \frac{\sqrt{D}}{\sqrt{L} \cdot \sqrt{\sigma'_{ave}}} + 0.023 \frac{\sqrt{D} \cdot \sqrt{\sigma'_{ave}} \cdot S_u}{\sqrt{L}} + 27.17$$
(18)

Figures 5a and b show the relationship between the predicted and measured skin friction values. It is clear from the figures that most of the points are on or very close to the no-error line, which means that the developed model provides very good prediction and providing further confidence in the developed MOGA-EPR model.

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430	Table 3: Statistics of the training	data used in the MOGA-EPR analysi	s
			-

Statistical	Parameter				
indicator	<i>L</i> (m)	<i>D</i> (cm)	σ_{ave}' (kPa)	S_u (kPa)	fs (kPa)
Mean	20.56	30.80	119.57	63.13	41.80
Standard	16.44	17.12	132.08	63.65	38.38
deviation					
Max.	96.00	76.70	718.00	335.00	192.10
Min.	4.60	11.40	19.00	9.00	8.00
Range	91.40	65.30	699.00	326.00	184.10

433 Table 4: Statistics of the testing data used in the MOGA-EPR analysis

Statistical	Parameter				
indicator	<i>L</i> (m)	<i>D</i> (cm)	σ_{ave}' (kPa)	S _u (kPa)	fs (kPa)
Mean	25.52	34.05	144.62	58.31	37.03
Standard deviation	16.08	14.69	110.94	44.50	28.83
Max.	66.40	61.00	448.00	185.00	109.20
Min.	9.40	15.00	49.00	17.00	12.00
Range	57.00	46.00	399.00	168.00	97.20





Figure 4: Results of the statistical analyses of the MOGA-EPR model: (a) Mean absolute error (*MAE*); (b) root mean square error (*RMSE*); (c) Mean (μ); (d) standard deviation (σ); (e) coefficient of determination (R^2); (f) variance account for (*VAF*); and (g) a20 - index

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Figure 5: Relationship between the MOGA-EPR predicted skin friction and measuredskin friction for: (a) training data; and (b) testing data

442 **7. Evaluation of the accuracy of the analytical methods**

It is very important to understand the limitations and the accuracy of the current
analytical methods. Thus, the accuracy of the previously discussed analytical methods
has been assessed in this section using the assessment methodology discussed

earlier in this paper. The results of the assessment have also been compared with the MOGA-EPR model. The β factor has been considered equal to 0.33 in the calculation of the skin friction capacity using the Beta method; this value is the average of the expected range for the β factor (Goh, 1995). Furthermore, the three methods mentioned previously to calculate the α factor have been considered in this assessment; the Sladen (1992) method has been named Alpha 1, the ISO method has been named Alpha 2, and the Terzaghi et al. method has been named Alpha 3.

Figures 6a, b, c, d, e, f and g show the obtained MAE, RMSE, μ , σ , R^2 , VAF and a20 -453 *index* for all of the analytical methods, respectively. In addition, Figures 7a, b, c, d and 454 e show the relationship of the predicted and measured skin friction for all of the 455 analytical methods. Comparing Figures 6 and 7 with Figures 4 and 5 clearly shows the 456 MOGA-EPR model predicts the skin friction capacity better than all of the other 457 analytical methods. Furthermore, Figure 6 shows that the Lambda method predicted 458 the skin friction with lowest error (Figures 6a and b), lowest standard deviation (Figure 459 460 6d), highest coefficient of determination (Figure 6e), highest value for the variance account for (Figure 6f) compared with the Alpha and Beta methods. However, the 461 mean (μ) of the Lambda method was relatively higher than the other methods (Figure 462 6c). Furthermore, the results of the mean (μ) show that, on average, all the analytical 463 methods tend to overestimate the skin friction of the pile except for the Alpha 3 method 464 which, on average, slightly underestimates the skin friction capacity. In addition, Figure 465 6g reveals that on average the Lambda, Alpha 1 and Alpha 2 methods produces 466 similar accuracy in terms of the percentage of the predictions with error equal to or 467 lower than 20%, where the scored a20 - index value is equal to 0.60, 0.62 and 0.63 468 for Lambda, Alpha 1 and Alpha 2 methods, respectively. Figures 7a, b, c, d and e 469 show that Lambda method provides less scatter around the mean compared with the 470 Alpha and Beta methods and this is confirmed by the obtained coefficient of 471 determination and *VAF*, which is higher for the Lambda method as shown in Figures 472 473 6e and f.

It is also obvious from Figure 6 that the Alpha 1 and Alpha 2 methods predict the skin friction capacity with slightly higher *MAE* (8.9 for Alpha 1 and 8.1 for Alpha 2), *RMSE* (14.4 for Alpha 1 and 13.0 for Alpha 2) and σ (0.32 for Alpha 1 and 0.27 for Alpha 2) compared than the Lambda method. In addition, the Alpha 1 and Alpha 2 methods predict the skin friction capacity with slightly lower R^2 (0.85 for Alpha 1 and 0.88 for Alpha 2) and *VAF* (85 for Alpha 1 and 88 for Alpha 2) than the Lambda method. The Alpha 1 and Alpha 2 methods also achieved a μ value closer to 1 (μ = 1.02 for the Alpha 1 method and μ = 1.07 for the Alpha 2 method) compared with the Lambda method (μ = 1.16). Thus, the Alpha 1 and Alpha 2 methods can be both ranked second compared with other analytical methods.

Finally, Figures 6 and 7 also show that the Beta method is the worst performing 484 method and the error produced using this method is very high (MAE = 17.2 and 485 *RMSE* = 28.0) compared with other methods. Also, the σ value obtained using the Beta 486 method is 1.00; this means a maximum scatter around the mean and can also be 487 confirmed by the very low coefficient of determination calculated using this method, 488 which is equal to 0.55 (Figure 6e) and the very low VAF, which is equal to 40 (Figure 489 6f). The very low coefficient of determination of the Beta method can also be evidenced 490 by Figure 7e, which shows a large scatter of the predicted-measured relationship 491 compared with the no-error line. Also, the a20 - index for the Beta method is very low 492 and is equal to 0.37; this means only 37% of the predictions are with error equal to or 493 less than 20%. Hence, the Beta method ranked last based on this assessment. 494





Figure 6: Results of the statistical analysis: (a) Mean absolute error (*MAE*); (b) root mean square error (*RMSE*); (c) Mean (μ); (d) standard deviation (σ); and (e) coefficient of determination (R^2); (f) Variance account for (*VAF*); and (g) a20 - index





500 8. Conclusions

501 The results of this study have demonstrated the abilities of the multi-objective 502 evolutionary (MOGA-EPR) polynomial regression analysis in predicting the skin 503 friction capacity of driven piles embedded in clay. The MOGA-EPR model achieved a

very low error, a mean value close to 1, low standard deviation, very high coefficient 504 of determination, very high value for the variance account for and high value for the 505 a20 - index for both training and testing data. Furthermore, the accuracy of the 506 MOGA-EPR model has been confirmed by presenting the relationship between the 507 predicted and measured skin friction values for both the training and testing data and 508 the presented relationships demonstrated the accuracy of the MOGA-EPR model as 509 most of the points were on or very close to the no-error line for both the testing and 510 training data. In addition, the MOGA-EPR model has been compared with the available 511 analytical methods in the literature and the results have demonstrated that the 512 developed model is better than the available analytical methods as the MOGA-EPR 513 model performed better based on the statistical measures. Thus, the developed model 514 can be used with confidence in future designs. However, it is worth stating that the 515 developed model has been trained and tested based on lengths of pile ranging from 516 517 4.60 m to 96.00 m, diameters of piles ranging from 11.40 cm to 76.70 cm and undrained cohesion ranging from 9.00 kPa to 355 kPa. Hence, the model should be 518 519 used for designs within these ranges. Nonetheless, the developed model can also be tested further in the future when new data becomes available. 520

In addition, assessing the available analytical methods showed that the Lambda 521 method is the most accurate method compared with Alpha and Beta methods. This 522 method scored an mean absolute error (*MAE*) of 7.8, a root mean square error (*RMSE*) 523 of 12.5, a mean (μ) of 1.16, a standard deviation (σ) of 0.21, a coefficient of 524 determination (R^2) of 0.91, a value for the variance account for (VAF) of 89 and a20 - a20525 index of 0.6. Hence, this method can also be used as an alternative to the MOGA-526 EPR model developed in this study. Furthermore, the Alpha 1 method (Sladen, 1992) 527 528 and Alpha 2 method (ISO, 2016) also scored low errors and high coefficient of determination; the errors of both methods are slightly higher than the Lambda method. 529 530 The Alpha 1 and Alpha 2 methods also scored a μ closer to 1 than the Lambda method; therefore, both methods can be ranked second. The Beta method scored lowest 531 compared with the other analytical methods with a *MAE* of 17.2, a *RMSE* of 28.0, a μ 532 of 1.07, a σ of 1.00, a R^2 of 0.55, a VAF of 40 and a20 - index of 0.37. The developed 533 mathematical model in this paper and the results of the assessment of the analytical 534 535 methods are very useful to geotechnical engineers and will help to achieve better pile 536 designs in the future.

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