Modeling oblique load carrying capacity of batter pile groups using neural network, random forest regression and M5 model tree

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ABSTRACT M5model tree, Random forest regression (RF) and Neural network (NN) based modelling approaches were used to predict oblique load carrying capacity of batter pile groups using 247 laboratory experiments with smooth and rough pile groups. Pile length *(L)*,angle of oblique load (α), sand density (*ρ*), number of batter piles (*B*) and number of vertical piles (*V*)as input and oblique load (Q)as output was used. Results suggest improved performance by random forest (RF) regression for both pile groups. M5 model tree provide simple linear relation which can be used for the prediction of oblique load for field data also. Model developed using Random forest regression approach with smooth pile group data was found to be in good agreement for rough piles data. Neural network (NN) based approach was found performing equally well with both smooth and rough piles. Sensitivity analysis using all three modelling approaches suggest angle of oblique load (*α*) and number of batter pile (*B*) affect the oblique load capacity for both smooth and rough pile groups.

KEYWORDS batter piles, oblique load test, neural network, M5 model tree, random forest regression, ANOVA

1 Introduction

The use of pile foundations is widespread when the soil below the structure is not capable of supporting the superstructure. Vertical piles are capable of resisting large amount of vertical load and small amount of lateral load, but high rise building, offshore structure, earth retaining structure and earthquake prone structure are subjected to large amount of load due to action of wind, water, earth and earthquake forces in lateral direction. When lateral load exceeds the limiting capacity of vertical piles, batter piles are used in combination to vertical piles. Batter piles are inclined piles and are capable of resisting lateral load as these piles convert overturning movement generated due to lateral load to compression and tension forces. Depending upon the direction of application of lateral load, batter piles are classified into negative batter piles (when subjected to lateral load in the direction of batter) and positive batter piles (when subjected to lateral load opposite to the direction of batter).

Study carried out by Tschebotarioff [1] using model studies suggested that slip surface deflect upward and downward in case of positive and negative batter piles respectively whereas Murthy[2] and Prakash and Subramanyam [3] concluded that under lateral load negative batter pile offer greater resistance in comparison to positive batter piles. Ranjan et al [4] also concluded that negative batter pile is more efficient in handling load than positive batter piles. Lu [5] carried out lateral load test and suggested that in case of negative batter soil reaction at ground level is maximum whereas zero in case of positive batter pile hence upper layer soil support negative batter pile. Veeresh [6] conducted cyclic lateral load test on batter pile and suggested that soil strength decreases in case of positive batter pile because a gap was formed behind the pile due to slippage of pile, whereas slippage occur into the gap in case of negative batter pile. Hence it can be concluded that in case batter pile are subjected to lateral loads, negative batter pile are more efficient than vertical and positive batter pile.

Effect of pile inclination on its load carrying capacity was studied by various researchers to obtain the most efficient batter angle. Meyerhof [7] suggested that the capacity of batter pile under vertical load decreases with increase in pile inclination. Awad and Ayoub [8] conducted axial pullout test on model pile and results were in accordance of Meyerhof [9] Chattopadhyay and Pise [10] concluded that ultimate pullout capacity of batter piles increase initially with increase in pile inclination with maximum value reaching between 15° and 22.5º and found a decreasing trend in capacity with further increase in pile inclination. Bose and Krishnan [11] concluded from their experimental investigation that pullout capacity of batter pile increases with increase in pile inclination up to an angle of 20° and start decreasing with further increase in pile inclination. Nazir and Nasr [12] carried out model test on batter piles under axial uplift forces and concluded that batter piles inclined at 20° gives better performance than those incline at 10° and 30°. Sharma et al [13] conducted model study on vertical and battered micropile under vertical and lateral loading and concluded negative micropile with 15° and 30° shows greater resistance than vertical and positive batter piles and negative batter pile at 45° batter angle because of these contradictory findings, further study is required to investigate the effect of batter on load bearing capacity of batter pile under lateral loading.

As batter pile are also subjected to vertical load in addition to lateral load resulting in inclined load on batter piles. Various researchers studied the behaviour of batter pile under inclined load. Teng et al [14] carried out model test on batter pile under oblique pullout load and concluded that negative batter pile offer more pullout resistance than vertical or positive batter piles. Meyerhof [9] conducted experiments on batter pilesunder inclined load (i.e. 0°,30°,60° and 90°) and concluded that ultimate pullout capacity of vertical and negative batter pile increases as load inclination with pile axis increases. In case of positive batter piles, their results suggests a decreasing trend up to 60° of load inclination but increases afterward with further increase of load inclination. Al-Shakarchi et al[15] inferred from model studies on vertical and batter piles that pullout capacity of vertical and batter pile increases as load inclination increases up to 45° beyond which negative batter piles exceeds the capacity of vertical pile, and positive batter pile have lower pullout capacity than vertical and negative batter pile at all load inclination. Mroueh and Shahrour [16] conducted three dimensional nonlinear finite element analysis on vertical and batter pile (± 10°, ± 20°) and found that ultimate pullout capacity continuously decreases with increase in load inclination for vertical, negative and positive batter piles and the decreases was significant from 0° to 10°. Bhardwaj and Singh [17] carried out model test on vertical and battered micropile and conclude that ultimate capacity decreases as load inclination increases with the micropile axis and negative micropile offer greater resistance than vertical and positive batter pile at all load inclination. It can be concluded from the above studies that the results by different researchers are contradictory thus suggesting the need of further investigation to understand the effect of oblique load on batter pile.

As laboratory analysis involve high cost and labour, various researchers developed different theoretical and numerical methods to determine the load bearing capacity of batter piles. Rajashree [18] applied nonlinear finite-element modelling of batter piles under lateral load and concluded that capacity of negative batter piles under static as well as cyclic load were more than positive piles. In case of negative batter piles soil strength was found to degrade slowly than the positive batter piles. Sabry [19] inferred from his numerical modelling that if $\phi > 30°$ (ϕ= angle of internal friction) the pile capacity increases with increase in pile inclination and if $\phi < 30°$ the pile capacity decreases with increase in pile inclination. Hanna and Sabry [20] concluded from theoretical modelling that axial pullout capacity increases, remain constant or decrease with increase in pile inclination for dense, medium or loose sands respectively. Giannakou et al [21] carried out three dimensional finite element modelling to determine the condition under which batter pile severs best, from the study it was found that the total kinematic plus inertial response of structural systems supported on groups of batter piles offers many reasons for optimism. However few works have reported the use of numerical modelling on batter pile in comparison to vertical piles. Effects of oblique load on vertical piles were studied by Johnson [22], Ramadan et al [23], Achmus and Thieken [24] and also lateral capacity of vertical piles was studied by Trochains [25], Rajashree [26], Rajashree [27]. Despite of the cost effectiveness, numerical methods are time consuming hence their uses are limited.

Various researchers have reported the used of several machine learning techniques for prediction of pile capacity. These techniques require less computational resources and found to be simple in comparison to numerical modelling approaches. Chan[28], Chow[29], Goh [30], Teh [31],Lok and Che [32] used artificial neural network with both static and dynamic data set to predict the load bearing capacity of piles and compared the results with available empirical and found that results are similar or better than the available empirical equations. Etemad–Shahidi and Ghaemi [33], Pal et al [34] used M5 model tree and Random forest (RF) regression approach for prediction of pier scour modelling and found both approaches well suited for pier scour modelling. M5 model tree and RF regression approach were applied to civil engineering problems: Singh et al [35] in prediction of Road accident, Bhattacharya &Solomatine [36] for modelling water level-discharge, Solomatine and Xue [37] for flood forecasting, Leshem and Ritov [38] for traffic flow prediction and found it to be performing well for different civil engineering problems. Keeping in view the effectiveness of M5 and RF based regression approaches, present study aims to examine the potential of these approaches for modelling the oblique load capacity of batter pile groups and comparing their performance with widely used neural network approach.

To analyse the influence of different input parameters (i.e. number of vertical piles, number of batter piles, angle of oblique load, pile length and sand density) on pile capacity using different machine learning algorithms, a sensitivity analysis has been carried. The purpose of sensitivity analysis in this study is not to change the value of one input parameter by keeping other fixed, as used with simple and hybrid surrogate models (Hamdia et al., [39]; Badwey et. al., [40]; Hamdia et al. [41]) but to remove one input parameter in each trial and note its influence on the pile capacity. Several other regression and sensitivity analysis approaches are proposed in literature and can be used as an alternate to the proposed approaches (Vu-Bac et al., [42-46]

2 Detail of model used

2.1 M5 Model Tree:

M5 model Tree is a binary decision tree that uses linear regression function at the leaf (terminal node) which helps in predicting continuous numerical attributes. This method involves two stages for generation of model tree. First stage consists of splitting criteria to generate a decision tree. Splitting criteria for this method is based on treating the standard deviation of class value. Splitting process cause less standard deviation in child node as compared to parent node and thus more pure Quinlan [47] Out of all possible splits, M5 model tree opt the one that maximize the error reductions. This process of splitting the data may overgrow the tree which may cause over fitting. So, the next stage involves in removing over fitting using pruning method. It prunes back overgrown trees by substituting the sub trees with linear regression function. In this technique of tree generation, parameter space is split into surfaces and building a linear regression model in each of them.

M5 model tree algorithm utilizes standard deviation of the class value reaching at terminal node which measures of the error value at that node and evaluates the expected reduction in error. Formula for standard reduction formula is given as

$$SDR = sd(N) - \sum \frac{|N_I|}{|N|} sd(N_i), \tag{1}$$

where N depicts a set of examples that arrive at the node. N_i depicts i^{th} outcome of subset of examples of potential set and sd is standard deviation.

2.2 Random Forest (RF)

Random forest (RF) regression approach consists of a combination of tree predictors where each tree is generated from the input vector using a random vector sampled independently. Random forest regression consists of combination of variables at each node to grow a tree or using randomly selected input variable as used in present study. To generate a training data set, bagging , which randomly draw I training samples with replacement, where I is the size of the original training set (Breiman,[48], or a randomly selected part of the training set is used for the construction of individual trees for a random feature combination. In case of bagging (bootstrap sample), about one-third of the data are left out from every tree grown thus training set consists of about 67% of original training set whereas the left out data are called out-of-bag (out of the bootstrap sampling). Random forest uses the Gini Index (Brieman et. al., [49] as attribute selection measure which measures the impurity of the variable compared to the output.

Two user-defined parameters are required for random forest regression: number of input variables (m) used at each node to generate a tree and the number of trees to be grown (k) (Breiman, [49]). At each node, only selected variables are searched through for the best split. Thus, the random forest regression consists of k trees.

2.3 Neural Network (NN)

Neural network (NN) has widely been used for numerical prediction of pile capacity (Ismail, A. et al 2013; Shahin, M. A. 2014; Zhang, W., & Goh, A. T. C. 2014). It is inspired by the functioning of nervous system and brain architecture. NN have one input, one or more hidden and one output layer. Each layer consists of number of nodes and the weighted connection between these layers represents the link between nodes. Input layer having nodes equal to the number of input parameters, distributes the data presented to the network and doesn't helps in processing. This layer follows one or more hidden layer which helps in processing of data. The output layer is final processing unit. When an input layer is subjected to a input value which passes through the interconnections between nodes, these values are multiplied by the corresponding weight and summed to obtain the net output (z_j) to the unit

$$z_j = \sum_i W_{ij} * y_i \tag{2}$$

where, W_{ij} is weigh of interconnection from unit$i$ to j, y_i is the input value at input layer, $z_j$is output obtained by activation function to produce an output for unit j. The detailed discussion about NN is provided Haykin (1999). In present analysis a three-layer feed forward multilayer perceptron (MLP) NN based on the back propagation algorithm is used.

3 Methodology and Data set

Data used in this study was obtained from experimental investigations carried out in soil mechanics lab of National Institute of Technology Kurukshetra (India). A steel tank with dimension of 1m×2m×1m with wall thickness of 5mm was used. It has special pulley arrangement whose height may be altered so, when rope passes over it, desired loading angle (0º,10º 20º, 30º,45º) with horizontal axis can be obtained (Fig. 1). The tank was filled using rainfall method of sand filling and tests were carried out on poorly graded sand (Table 1) at two densities 15.79kN/m^3 and 16.28kN/m^3. Fig. 2 gives particle size distribution curve for sand.

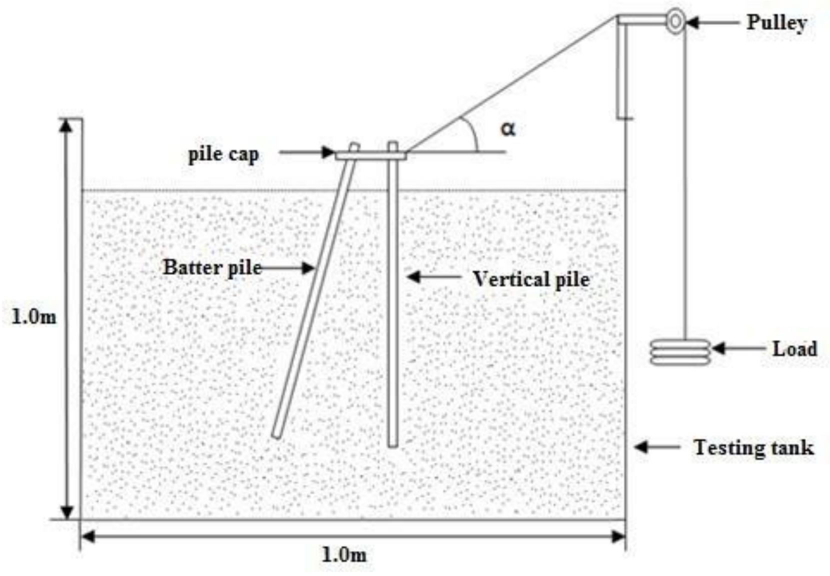


Fig. 1 Model setup

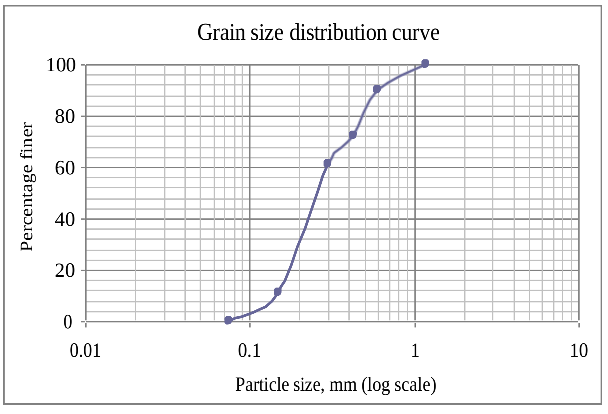


Fig. 2 Particle size distribution curve for sand

Table 1 Properties of sand

S.NO.	Properties	Values
1	Soil Type	SP
2	Effective size (D_{10})in mm	0.175
3	Uniformity coefficient (C_u)	2
4	Coefficient of curvature (C_c)	3.84
5	Specific gravity (G)	2.63
6	Minimum dry density (γ_{dmin}) in KN/m3	14.3
7	Maximum dry density (γ_{dmax}) in KN/m3	17.3
8	Maximum void ratio, e_{max}	0.84
9	Minimum void ratio, e_{min}	0.52

Model piles used in this study were of two types (Fig. 3) viz. smooth piles (roughness R_a=0.254µm)and rough piles (roughness R_a=6.237µm). For smooth piles, aluminium pipes were used having 0.90 m, 0.60 m and 0.40 m length, with outer diameter 20 mm and wall thickness of 1mm were used. Rough piles were produced by gluing sand on aluminium piles of 0.60 m and 0.40 m length. Roughness of both pile were measured using Surfcom Flex, this device measures the surface texture, when needle of this instrument was placed on smooth and rough pile, roughness of the surface was indicated in display.

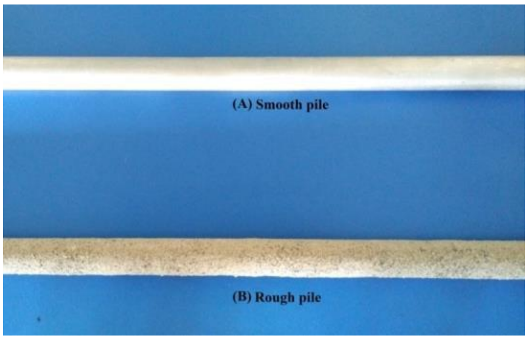


Fig. 3 Two pile surface

Piles caps (Fig. 4) were used to keep all piles in groups and for equal distribution of loads and to guide batter piles at proper angle. Five pile caps were fabricated having 20mm thickness with vertical and 25º batter hole, 0.20m extra length on sides of holes was also provided to attach thick steel hooks to fix the wire passing over the pulley.

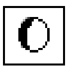
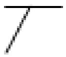
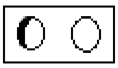
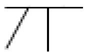
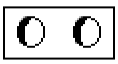
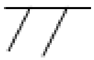
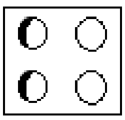
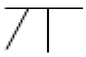
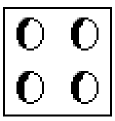
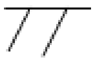
Test Series	**Plan**	**Elevation**	**Loading direction**	**No. of vertical piles**	**No. of batter piles**
1			→	-	1(-ve)
2			→	1	1(-ve)
3			→	-	2(-ve)
4			→	2	2(-ve)
5			→	-	4(-ve)

Fig. 4 Plan of pile caps

Testing procedure consists of placing pile caps at the centre of the tank, so that batter and vertical piles can be installed accurately by gentle tapping at the top. Height of the pulley was adjusted to attain the desired angle with horizontal axis (Fig.1). To measure the deflection, dial gauge were attached to pile caps in the direction of loading angle.

Loads were applied until the deflection value reaches between 10-15mm. The unloading and reloading of load was done in each experiment in same manner and deflection value was measured. This way a total of 247 experiments were conducted with both smooth and rough pile groups (147 with smooth piles and 100 with rough piles). Table 2 provides summary to test performed on smooth and rough pile groups. The notation for pile caps used are given as; *1B*: one batter pile, *1B1V*: groups of one vertical and one batter pile, *2B*: groups of two batter piles, *2V2B*: groups of two vertical and two batter pile, *4B*: four batter piles.

Table 2 Summary of test performed

Constant Parameter				Variable Parameter
ρ(kN/m^3)	α°	L(m)	Pile surface	Pile groups
16.28	0	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	0	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	0	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	10	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	10	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	10	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	20	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	20	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	20	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	30	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	30	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	30	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	45	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	45	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
16.28	45	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	0	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	0	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	0	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	10	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	10	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	10	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	20	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	20	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	20	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	30	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	30	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	30	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	45	0.40	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	45	0.60	Smooth	1B, 1V1B, 2B, 2V2B, 4B
15.79	45	0.90	Smooth	1B, 1V1B, 2B, 2V2B, 4B

16.28	0	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	0	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	10	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	10	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	20	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	20	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	30	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	30	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	45	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
16.28	45	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	0	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	0	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	10	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	10	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	20	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	20	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	30	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	30	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	45	0.40	Rough	1B, 1V1B, 2B, 2V2B, 4B
15.79	45	0.60	Rough	1B, 1V1B, 2B, 2V2B, 4B

4 Analysis and detail of M5, RF and NN

To model the oblique load (Q_α) using M5, RF and NN approaches, number of vertical pile (V), number of batter pile (B), angle of oblique load (α) in degree, pile length (L) in m, sand density (ρ) in kN/m^3 were used as input parameters. Analysis was carried out in three different ways. First analysis (set 1) consists of using data from smooth pile groups. In this case, a total of 105 randomly selected data were used for training and rest of 42 data were used for testing. Second analysis (Set 2) consists of 100 results on rough pile groups. Similar to smooth pile groups about 2/3 (i.e. 70) randomly selected samples were used for training whereas rest of 30 samples were used for testing the models. Set 3 analyses consist of using models developed by different approaches using training data of smooth pile groups (i.e. 105 samples) and testing all samples of rough piles groups (i.e. 30 samples). Summary of smooth and rough pile groups datasets used are provided in Tables 3 and 4.

Table 3 Summary of training and testing data set for smooth piles

Input parameters	**Training data set**				**Testing data set**			
	Min	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**
α	0.00	45.00	20.905	15.793	0.00	45.00	22.024	15.659
L	0.40	0.90	0.638	0.207	0.40	0.90	0.638	0.205
V	0.00	2.00	0.60	0.804	0.00	2.00	0.643	0.821
B	1.00	4.00	2.019	1.118	1.00	4.00	2.024	1.07
ρ	15.79	16.28	16.032	0.246	15.79	16.28	16.058	0.246

Table 4 Summary of training and testing data set for rough piles

Input parameters	Training data set				Testing data set			
	Min	**Max**	**Mean**	**Std. dev.**	**Min**	**Max**	**Mean**	**Std. dev.**
α	0	45	20.571	15.892	0	45	22	15.46
L	0.40	0.60	0.497	10.07	0.40	0.60	.507	0.101
V	0	2	0.657	0.814	0	2	0.467	0.776
B	1	4	1.943	1.048	1	4	2.133	1.224
ρ	15.79	16.28	16.042	0.246	15.79	16.28	16.018	0.248

Large numbers of trials were carried out to select optimal value of user defined parameter for different modelling approaches. Table 5 provide the optimal value of user defined parameters with M5 model tree, RF and NN approaches. For quantitative comparison of performance of different regression approach, correlation coefficient (*CC*) and root mean square error (*RMSE*) values were used. For statistical comparison of predicted values ANOVA single factor test was carried out

ANOVA (analysis of variance), single factor test, is a method for comparing multiple means across different groups. It is a hypothesis testing technique to examine whether statistically significant differences in means occur among two or more groups. In ANOVA, single factor test (or one way ANOVA) consider only one factor and suggest that if means are statically significant or not.

From ANOVA single factor test we obtain *F-value*, *F-critical* and *p-value*. *F-value obtained is lesser than F-critical*, then the difference among the group is said to be statically insignificant and vise versa. Similarly, if *p-value* obtained is greater than 0.05 then again difference among the group is said to be statistically insignificant and vise versa. For detail reader can refer to Zikumund et al (2013)

Table 5 Optimal values of user defined parameter

Classifier used	**User-defined parameters**	**Pile Group**
M5 model tree	Number of training examples allowed at a terminal node=4	smooth
RF	*k*= 1, *m*= 1, where *k* is number of trees an *m* means number of input parameters	smooth
NN	Learning rate =0.3, momentum =0.2, hidden nodes =8, number of iterations =200	smooth
M5 model tree	Number of training examples allowed at a terminal node=4	rough
RF	*k*= 2, *m*= 1, where *k* is number of trees an *m* means number of input parameters	rough
NN	Learning rate =0.3, momentum =0.2, hidden nodes =8, number of iterations =200	rough

5. Result and Discussion

5.1 Smooth pile groups (Set1)

Fig 5(a) to (c) provides a plot of actual vs. predicted oblique load using M5 model tree, RF and NN modelling approaches on testing data. Comparison of correlation coefficient (*CC*) and root mean square error (*RMSE*) values indicate that RF based modelling approach provide slightly improved performance than M5 model tree and NN approaches (Table 6). ANOVA single factor test was used to compare statistical difference of predicted value from actual value by all three modelling approaches. Results from Table 7 suggests that *F-value* was less than *f-critical* and *P-value* was greater than 0.05 suggesting that difference in predicted values was insignificant for all three modelling approaches. Despite of the inferior performance (but not statistically significant) by M5 model tree in comparison to other two approaches, it provides a model in form of a simple linear relation (equation 3) which can easily be used by field engineers within the given range of input variables

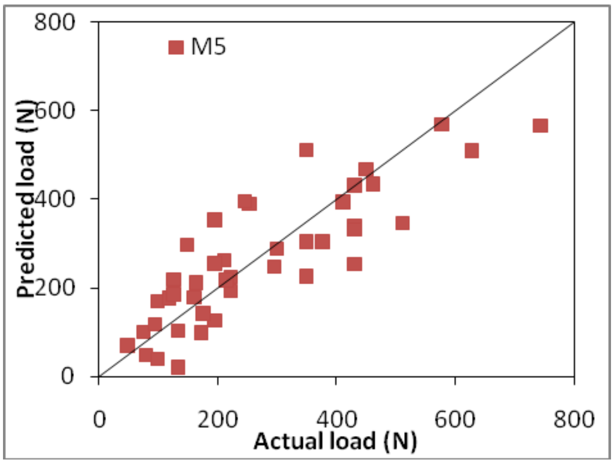
*q*3)

$$Q_{\alpha smooth} = 3.91\alpha + 57.1735V + 109.3825B + 0.2054\rho - 3601.4102 \quad (3)$$

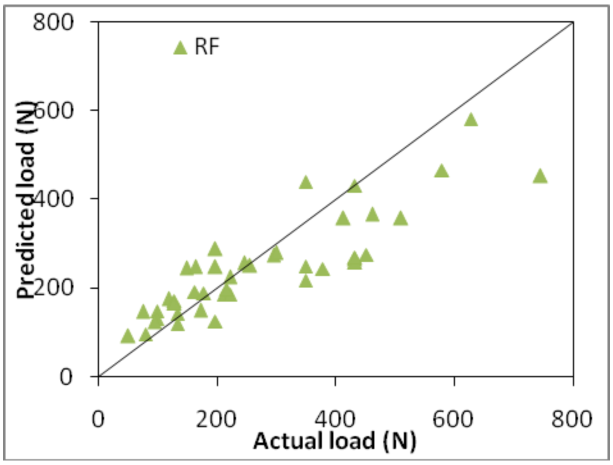
$Q_{\alpha smooth}$ *is* oblique load carrying capacity for smooth pile groups

Table 6 Detail of performance evaluation parameters using M5, RF and NN for testing data on all three set of results

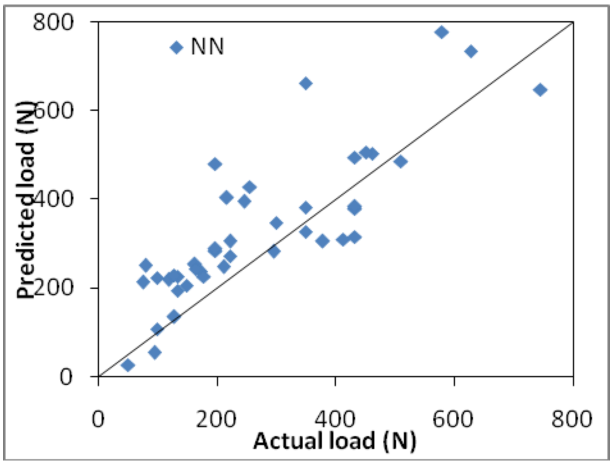
Testing Set	Regression Approach	CC	RMSE(N)
Set 1	M5	0.8466	87.8963
Set 1	RF	0.8667	92.6711
Set 1	NN	0.8369	112.0335
Set 2	M5	0.858	120.7983
Set 2	RF	0.8910	109.6845
Set 2	NN	0.8730	117.2033
Set 3	M5	0.8329	141.9502
Set 3	RF	0.9128	117.6547
Set 3	NN	0.8839	121.6179



(a)



(b)



(c)

Fig. 5 Plot between actual vs. predicted load using modelling approaches using smooth piles (set 1) (a) M5; (b) RF; (c) NN.

Table 7 Results of ANOVA: single factor test

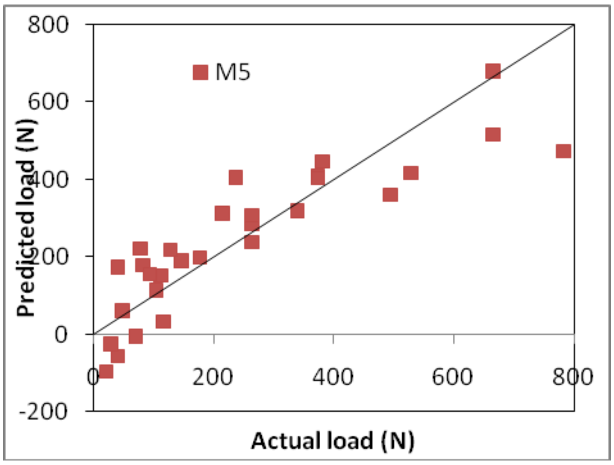
Set	Modeling approach	*F-value*	*F critical*	*P value*
Set 1	NN	2.80715	3.957388	0.097654
Set 1	M5P	0.054662	3.957388	0.815724
Set 1	RF	0.804006	3.957388	0.372523
Set 2	NN	0.184121	4.006873	0.669445
Set 2	M5P	0.071353	4.006873	0.790325
Set 2	RF	0.001861	4.006873	0.96574
Set 3	NN	0.367833	4.006873	0.546555
Set 3	M5P	1.049788	4.006873	0.30981
Set 3	RF	0.480682	4.006873	0.490881

5.2 Rough pile groups (Set 2)

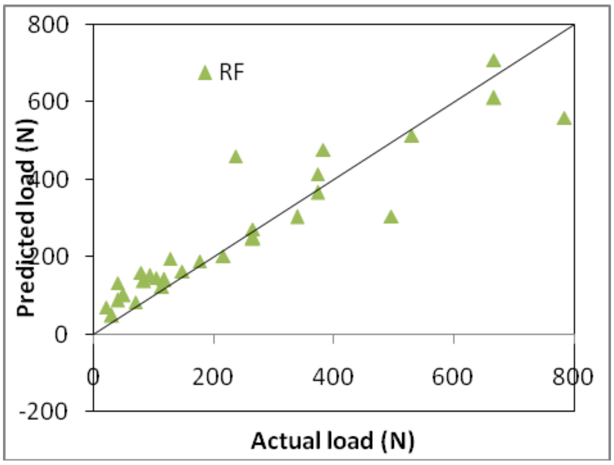
Seventy randomly selected samples as training data set and rest of 30 data set as testing data set, M5 model tree, RF and NN regression approaches were used for modelling the loading capacity of rough batter pile groups. Fig 6 (a) to (c) provides a plot between actual and predicted values of loading capacity using testing data. Comparison of results in terms of *CC* and *RMSE* (Table 6) indicates comparable performance by all three approaches with slightly better performance of RF approach. However results of ANOVA with single factor test results (Table 7) indicates that difference in predicted values by M5, RF and NN regression approach and actual values are statistically insignificant. Availability of few negative predicted values from M5 model tree is one limitation of this approach with rough pile groups. Similar to the smooth piles, M5 model tree provide a linear relation for rough pile groups (equation4):

$$Q_{\alpha rough} = 4.4101\alpha + 812.3253L + 130.02171V + 83.283B + 0.2285\rho - 4156.0067 \quad (4)$$

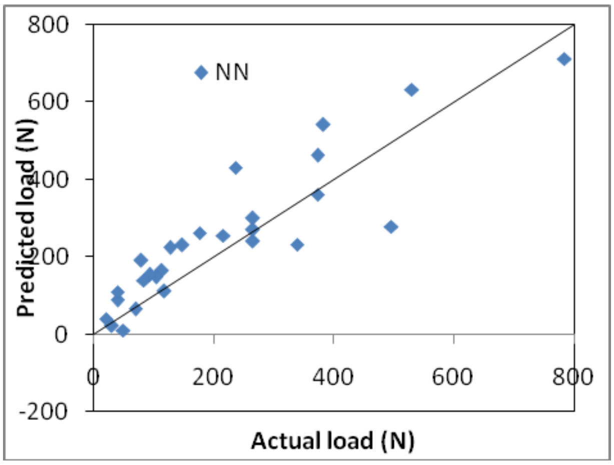
$Q_{\alpha rough}$ is oblique load carrying capacity for rough pile groups



(a)



(b)

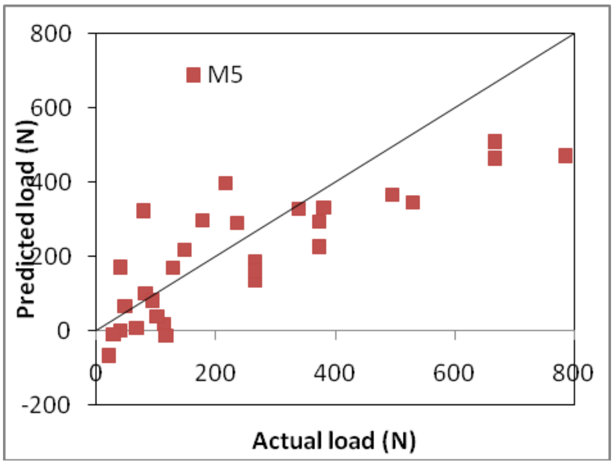


(c)

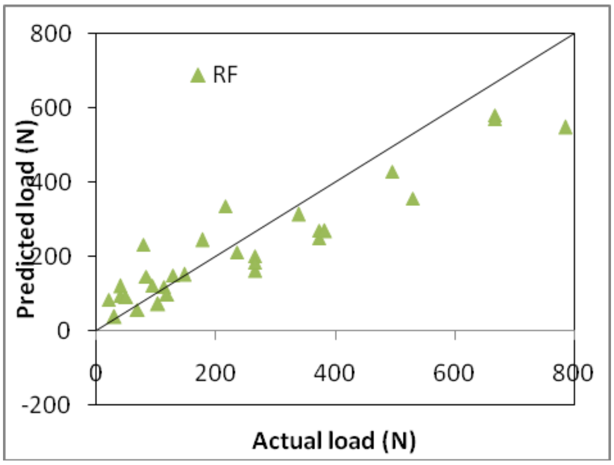
Fig. 6 Plot between actual vs. predicted load using modelling approaches using rough piles (set 1) (a) M5; (b) RF; (c) NN.

5.3 Training with smooth pile groups and testing with rough pile groups (Set 3)

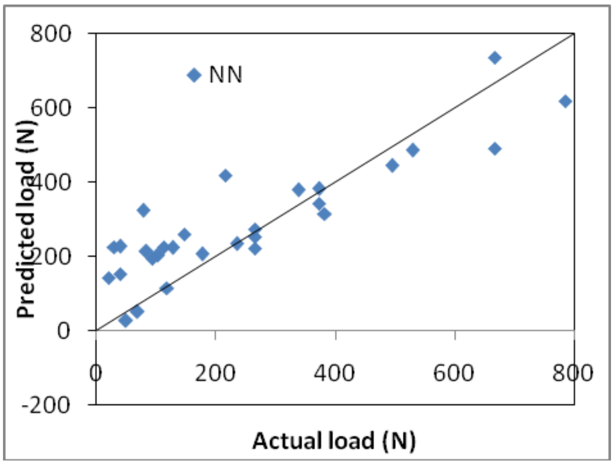
Keeping in view the encouraging performance by all modelling approaches with smooth pile groups dataset, this part of the study discusses about the performance of M5 model tree, RF and NN modelling approaches using smooth pile group's data for training and rough pile data for testing. Fig 7(a) to (c) provides a plot between actual and predicted values using testing data of rough piles. Results in terms of CC and RMSE (Table 6) indicate better performance by RF approach in comparison to M5 model tree and NN approaches with this combination of dataset. Results from ANOVA test (Table 7) again indicates no significant difference in performance of all three approaches from actual value. Availability of few negative predicted values by M5 model tree with this combination of training and test dataset suggests its limitations with rough piles.



(a)



(b)



(c)

Fig. 6 Plot between actual vs. predicted load using modelling approaches for set 3 (a) M5; (b) RF; (c) NN.

6 Sensitivity Analyses

Sensitivity analysis was carried out to determine the relative importance of each input parameter. In present case, sensitivity analysis was used to determine the most important parameter which contributes to the pile capacity out of five input parameters using M5 model tree, RF and NN approaches. This was achieved by creating new datasets by removing one parameter from input in each trial and keeping other parameter constant and models were generated using new training datasets and process is repeated for each input parameters Singh et al (2016), Pal et al (2013). Correlation coefficient (*CC*) and root mean square error (*RMSE*) values obtained were compared to judge the influence of removal of different parameters on model performance (Table 8) Amount of increase in *RMSE* value and decrease in *CC* values indicate that comparative importance of each factor, if difference in *RMSE* value and *CC* value from actual is large after removal of any parameter shows that parameter is very important and vice versa.

Results from Table 8 indicate that number of batter piles (*B*) is the most important parameter in resisting oblique load on batter piles with all three modelling approaches used in this study. A possible reason may be that in case of smooth pile groups lateral load component of oblique load was resisted only by the batter piles only. Next important parameter was found to be pile length (*L*) and angle of oblique load (α) respectively.

Sensitivity analysis was carried out using all three approaches for rough pile groups also. Results from Table 8 indicates that angle of oblique load (α) seems to be the most important parameter in resisting oblique load whereas next important parameter were number of vertical pile (*V*) and number of batter pile (*B*) respectively.

Table 8 Sensitivity analysis using RF, NN and M5 modelling approach

parameter removed	**RF**		**NN**		**M5**	
	CC	**RMSE**	**CC**	**RMSE**	**CC**	**RMSE**
	0.9873	37.9796	0.892	119.180	0.821	109.993
α	0.8501	101.4785	0.795	120.110	0.756	126.010
L	0.838	105.284	0.768	123.594	0.732	131.319
V	0.955	59.961	0.892	87.453	0.789	118.475
B	0.745	128.769	0.617	165.234	0.539	162.269
ρ	0.895	86.603	0.829	121.195	0.779	120.716
	0.986	41.740	0.982	54.653	0.857	99.710
α	0.827	108.651	0.809	164.403	0.777	121.550
L	0.889	89.736	0.809	137.502	0.747	128.485
V	0.866	98.006	0.818	190.967	0.673	142.800
B	0.885	92.031	0.840	110.098	0.738	130.449
ρ	0.929	74.430	0.860	134.501	0.806	114.275

6 Conclusions

Three soft computing techniques were used to predict the oblique load capacity of batter pile groups. A major conclusion from this study is that all three approaches work well with present data and ANOVA-single factor test suggest that difference in actual and predicted values from each approach was insignificant for smooth pile group as well as rough pile group. Another conclusion from this study is that performance of RF regression approach was slightly better in both cases i.e. Smooth pile groups as well as rough pile groups, however model generated by RF regression on smooth pile groups was found to be in good agreement when tested with rough pile groups. So, it can be concluded that model generated by RF regression approach on smooth pile groups can be used for the prediction of oblique load capacity of both smooth as well as rough pile groups. Advantage of using M5 model was that it gives physically sound and simple linear equation which can be used for prediction of oblique load with given input range and does not require optimization of several user defined parameter. Results of sensitivity analysis on smooth pile groups suggest that in case of smooth pile group number of batter pile (B), angle of oblique load (α) and pile length (L) and in case of rough pile angle of oblique load (α), number of vertical pile (V) and number of batter pile (B) governs the oblique load capacity of pile groups.

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