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# Application of Random Forest Regression in the Prediction of Ultimate Bearing Capacity of Strip Footing Resting on Dense Sand Overlying Loose Sand Deposit

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## ABSTRACT

The paper presents the prediction of the ultimate bearing capacity of the strip footing resting on layered soil (dense sand overlying loose sand) using random forest regression (RFR). In this study, 181 data collected from literature were used. 71 % of the total data was randomly selected for training the model and the rest of the data were utilized for the testing purpose. The various input parameters were friction angle of the dense sand layer ($\phi_1$), friction angle of the loose sand layer ($\phi_2$), unit weight of the dense sand layer ($\gamma_1$), unit weight of the loose sand layer ($\gamma_2$), ratio of the thickness of the dense sand layer below base of the footing to the width of footing ($H/B$), ratio of the depth of the footing to the width of the footing ($D/B$) and $(H+D)/B$. Ultimate bearing capacity was the output in this study. Performance measures were used in order to make the comparison with the artificial neural network (ANN) and M5P model tree. The result of this study revealed that the performance of the RFR was superior to M5P and ANN. The results of the sensitivity analysis reveals that the unit weight and the friction angle of the loose sand layer were the most important parameters affecting the output ultimate bearing capacity of the strip footing resting on the layered soils.

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## 1. Introduction

In the foundation design, it is desired that the load of superstructure be transferred to the soil beneath the foundation safely without causing shear failure and excessive settlement. Many studies to determine the ultimate bearing capacity (UBC) of the footing resting over homogeneous soil were available in literature. But in actual field situation, the soil encountered was a layered soil. Various analytical and experimental methods were used to determine the UBC in such cases. Other approaches to determine the UBC of the footing resting over layered soil were classical approach [1–10], Semi empirical approach [1,3–5,10], Kinematic approach [2,8], Numerical approach [6], Finite element method [11–16]. Recently, researchers were focusing on the application of soft computing techniques such artificial neural network (*ANN*), support vector machine (*SVM*), random forest regression (RFR) and M5 model trees (*M5P*) in geotechnical engineering. Many studies related to the prediction of bearing capacity and settlement of the footings in different medium [17–20], deviator stress [21] bearing capacity of the strip footing resting on multilayered soil [22], geotechnical parameters [23], ultimate bearing capacity of the skirted and square footing on sand and confined sand [24,25], settlement of footings on cohesionless soils [26], horizontal stress [27], unsoaked and soaked bearing ratio [28] using ANN were available in literature. Studies related to prediction of pile capacity [29], settlement of footings on cohesionless soils [30], soil water content [31], soil classification and soil properties [32], soil moisture from remote sensing data [33] using SVM were available in literature. Very recently studies related to the prediction of pier scour [34] infiltration rate of soil [35] and geotechnical parameters [23] were reported using RFR and *M5P* in literature. These studies have concluded that the ANN, SVM, RFR and M5P satisfactorily able to model the geotechnical engineering problems. However, no study was available in literature to predict the ultimate bearing capacity of the strip footing resting on layered soil (dense sand overlying loose sand) using RFR, M5P and ANN in literature. This study tries to fill this gap. In the present paper application of RFR andM5P were used to predict the UBC of strip footing resting on layered soil (dense sand overlying loose sand). Finally, the performance of these two techniques was compared with the widely used *ANN* technique in geotechnical engineering.

## 2. Problem statement

The problem statement for the footing resting on layered soil to predict the UBC is shown in Fig. 1. The various input parameters affecting the ultimate bearing capacity ($q_u$) of the footing resting on layered soil were collected from the experimental and the finite element modeling results as reported in [4,36,37] and were given below.

1. Friction angle of the dense sand layer ($\phi_1$)
2. Friction angle of the loose sand layer ($\phi_2$)
3. Unit weight of the dense sand layer ($\gamma_1$)
4. Unit weight of the loose sand layer ($\gamma_2$)
5. Ratio of the thickness of the dense sand layer below base of the footing to the width of footing ($H/B$)
6. Ratio of the depth of the footing to the width of the footing ($D/B$)
7. $(H+D)/B$

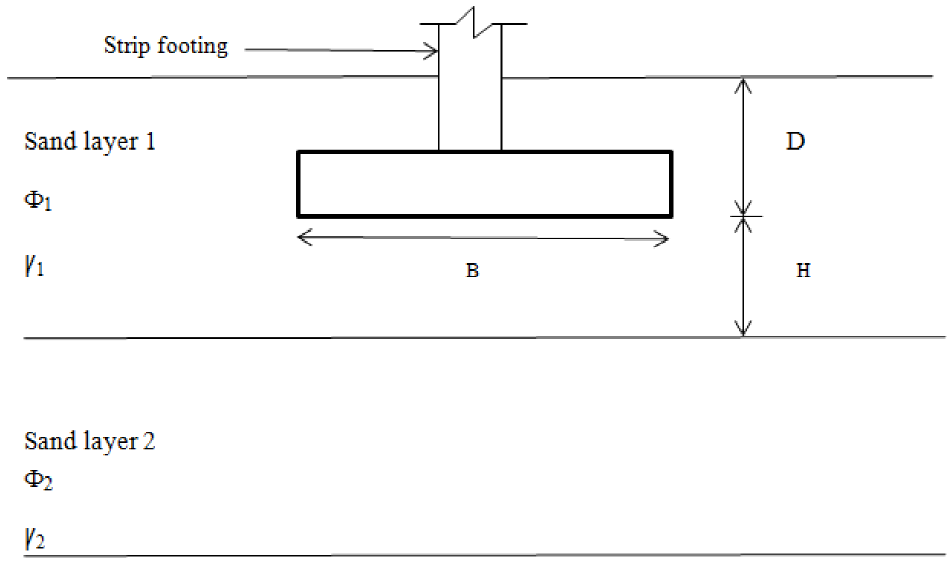


**Fig. 1.** Strip footing resting on layered soil.

## 3. Soft computing approaches

### 3.1. Random forest regression

The RFR is basically a regression and classification technique. This technique uses a combination of tree predictors. In this technique, each of the trees was generated using a random vector which was independently picked up from the input vector. Tree predictor takes on numerical values as opposed to classification labels used by the RF classifier [38]. For growing a tree, RFR uses a combination of parameters or selected parameter (chosen randomly) at each node. The training data is generated by bagging which is a technique where the data were randomly drawn and replaced with from the original data reserved for training. The training data can also randomly be selected for constructing an individual tree for each of the feature combination [39]. In bagging, 70 % of the original data was used for the training and 30 % was left out from every tree grown. A pruning method as well as a variable selection procedure was required in order to design a tree predictor. To select the variable for the tree induction, a large number approaches were available in literature. Majority of the approaches such as information gain ratio and Gini index in literature [39–41] recommends assigning a quality measure directly to the variable. RFR used in this study uses the former approach for the selection of the variable measure. The Gini index approach determines the impurity of the variable with respect to the output. RFR permits the tree to grow to the maximum depth of the training data by utilizing combination of variables and the fully grown trees were not allowed to be pruned back. This results in giving an edge to the RFR over the M5P as reported by [39]. Further, selection of variable measure as well as pruning method affects the performance of the tree based algorithm as reported by [41–43]. It was also reported by [38] that the generalization error converges with the increase in the number of trees even without pruning the tree. Also the overfitting of the data is not a problem due to strong law of large numbers as reported by [41]. For the RFR, the first user defined parameter required was numbers of trees to be developed (designated as *k*). The second parameter was the number of variables required to create a tree at each node (designated as *m*) as reported by [38]. Selected variables were searched through best split at each node. RFR thus contains k and m, which were defined by the user and can have any value. The output from the RFR was a numerical value and hence the mean square error can be obtained for the numerical predictor. RF predictor was formed by considering the average of the error over k number of trees.

## 3.2. M5P model tree

*M5P* model (a binary decision tree) uses a linear regression function having the ability to predict continuous numerical attributes at the terminal nodes (leaf) as reported by [40]. A divide and conquer technique was adopted to develop the tree-based models. Generation of model tree was done in two steps. A splitting criterion was adopted to make a decision tree in the first step. In the *M5P* model tree algorithm, the splitting criterion was based on the standard deviation of the class values. This standard deviation of the class values reaches at the node as a measure of the error at that node. Expected reduction during this error as a result of testing each of the attribute at that node was then calculated. The data in the child nodes has lesser standard deviation in comparison to the parent node due to the splitting process and thus considered more pure as reported by [40]. *M5P* picks up the one which maximizes the expected error reduction after examining the possible splits. Such division results into a large tree like structure leading to over fitting. The tree must be pruned back in order to avoid the over fitting and replacing the subspaces with the leaf of the tree. The second stage of the design of the model tree thus involves pruning and replacing the subspaces with linear regression function. The M5P splits the parameter into subspaces and develops a linear regression model in each of them. More details about the M5P can be had from [40].

## 3.3. Artificial neural network

Artificial neural network is regression model having the ability to predict the output of the non-linear input t in a precise manner. It has drawn inspiration from the functioning of human nervous system. In this study a feedforward back propagation algorithm has been used. A basic neural network was an inter connection of input, hidden and output layers where the weights and the bias have been generated between the input & hidden layer and between the hidden & output layer respectively. Initially, the input was selected which can be divided into training and testing data based on [21,24–28]. The training data was then used to train the neural network model and the iterations were fixed as per the procedure reported by [21,24–28]. The activation function used in the *ANN* was sigmoid function which was an inbuilt default function available in the open source Weka 3.8 software. Based on the literature [21] the sigmoid activation function has been proved to be the most accurate as it yields the minimum errors. Finally, the testing data was used to test the model. In order to check the accuracy of the predicted output with the actual output, the performance measures were calculated and discussed in the subsequent section.

## 4. Data set and performance measures

The random forest regression (*RFR*), *M5P* model tree and artificial neural network (*ANN*) based soft computing models were developed using an wide range of data comprising 91 experimental record (model plate load tests) and 90 theoretical record (two-dimensional finite element model) collected from different studies reported in literature [4,36,37]. The total data (181 records) were divided into two parts. The first part comprises of 128 records for the training purpose. The remaining data 53 records were used for the testing purpose. The selection of the data for the training as well as testing purpose was done randomly. It is pertinent to mention here that the division of the total data for the training and the testing was made based on the rules reported by [23,34,35]. The various input parameters used for the modelling were friction angle of first layer sand ($\phi_1$), friction angle of second layer sand ($\phi_2$), unit weight of first layer sand ($\gamma_1$), unit weight of second layer sand ($\gamma_2$), ratio of thickness of first layer sand below footing base to width of footing (*H/B*), ratio of depth of footing to width of footing (*D/B*) and (*H*+*D*)/*B* whereas the UBC was considered as an output. The range of each of the parameter considered in the study was given in Table 1.

**Table 1**
Range of the parameters used for modelling.

| Input parameters | Total data set | | | |
|---|---|---|---|---|
| | Min. | Max. | Avg. | Standard deviation |
| $\phi_1$ | 43.00 | 47.70 | 44.97 | 2.17 |
| $\phi_2$ | 30.00 | 42.40 | 36.68 | 3.87 |
| $\gamma_1$ (kN/m$^3$) | 16.34 | 20.00 | 18.82 | 1.43 |
| $\gamma_2$ (kN/m$^3$) | 13.00 | 19.00 | 16.60 | 2.06 |
| $(H+D)/B$ | 0.50 | 15.00 | 4.37 | 3.95 |
| $D/B$ | 0.00 | 1.00 | 0.07 | 0.23 |
| $H/B$ | 0.50 | 15.00 | 4.30 | 3.98 |
| $q_{ult}$ (kPa) | 41.02 | 4082.60 | 1765.19 | 1204.61 |

In order to check the prediction accuracy of the various soft computing techniques such as RFR, *M5P* and ANN, the various performance measures whose mathematical expressions tabulated in Table 2 were computed and compared.

The primary performance measures considered were the coefficient of determination ($R^2$) and the coefficient of correlation ($r$). The '$R^2$ and $r$' close to 1 indicating a best fit and 0 indicates a poor fit. The other performance measures such as *RMSE*, *MAE*, *RAE* and *RRSE* at the same time has to be minimum among the selected models for comparison. The lesser values of the *RMSE*, *MAE*, *RAE* and *RRSE* indicate the best model to predict the output. The calculated performance measures for the *RFR*, *M5P* and *ANN* were tabulated in Table 3.

**Table 2**
Performance measures and their mathematical expressions.

| Statistical coefficient | Mathematical expression |
|---|---|
| Correlation coefficient (r) | $r = \frac{\sum q_{ult_t} \times q_{ult_p} - n\bar{q}_{ult_t} \times q_{ult_p}}{(n-1)S_{q_{ult_t}} S_{q_{ult_p}}}$ |
| Coefficient of determination ($R^2$) | $R^2 = 1 - \frac{\sum_i (q_{ult_p} - q_{ult_t})^2}{\sum_i (q_{ult_p} - \bar{q}_{ult_p})^2}$ |
| Root mean square error (RMSE) | $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(q_{ult_t} - q_{ult_p})^2}$ |
| Mean absolute error (MAE) | $MAE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert q_{ult_t} - q_{ult_p}\right\rvert$ |
| Relative absolute error (RAE) | $RAE = \left[\sum_{i=1}^{n}\left\lvert\frac{q_{ult_p} - q_{ult_t}}{\bar{q}_{ult_t} - q_{ult_t}}\right\rvert\right] \times 100$ |
| Root relative square error (RRSE) | $RRSE = \sqrt{\frac{\sum_{i=1}^{n}\left(q_{ult_p} - q_{ult_t}\right)}{\sum_{i=1}^{n}\left(q_{ult_t} - \frac{1}{n}\sum_{i=1}^{n} q_{ult_t}\right)^2}}$ |

**Note**: $q_{ult_t}, q_{ult_p}$ target and predicted UBC respectively, $\bar{q}_{ult_t}, \bar{q}_{ult_p}$ :mean of the target and predicted UBC respectively, $S_{q_{ult_t}}, S_{q_{ult_p}}$ :standard deviation of the target and predicted UBC respectively, $n$ : number of observations

**Table 3**
Performance measures using RFR, M5P and ANN for the training and the testing data.

| Techniques | Training | | | | | | Testing | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | $R^2$ | *r* | *MAE* | *RMSE* | *RAE* | *RRSE* | $R^2$ | *r* | *MAE* | *RMSE* | *RAE* | *RRSE* |
| Random forest | 0.98 | 0.99 | 70.61 | 168.18 | 7.84 | 13.51 | 0.96 | 0.98 | 124.93 | 236.50 | 13.95 | 19.05 |
| M5 model tree | 0.47 | 0.91 | 512.52 | 645.96 | 56.88 | 51.88 | 0.31 | 0.85 | 551.69 | 708.90 | 61.60 | 57.12 |
| ANN | 0.94 | 0.97 | 380.23 | 467.07 | 42.20 | 37.51 | 0.94 | 0.97 | 378.77 | 460.65 | 42.29 | 37.11 |

It is pertinent to mention here that the selection of the optimal value of the user defined parameters affects the performance of the *RFR*, *M5P* model tree and *ANN*. The default user defined parameters in Weka software were initially used. The number of trials was carried out to find the optimal value of the user defined parameters by comparing the performance measures of each trial. Finally, the optimal user defined parameters were obtained and tabulated in the Table 4 for the RFR, M5P and ANN.

**Table 4**
Optimum values of user defined attributes for RFR, M5P and ANN.

| Classifiers used | User defined parameters |
|---|---|
| RFR | *k*=2, *m*=2, *I*=100 |
| M5P | *M*=5 |
| ANN | Learning rate = 0.2, momentum = 0.1, Iterations = 4000 Hidden layers = 5 |

## 5. Results and discussions

In order to compare the performance of the selected soft computing techniques for the prediction of the UBC of the strip footing resting on layered soil, performance measures such as $R^2$, $r$, *MAE*, *RMSE*, *MAE* and *RRSE* were calculated and were tabulated in Table 3. The predicted and targeted UBC using RFR, *M5P* and ANN techniques for the training and the testing data were shown in Figs. 2-4 respectively.

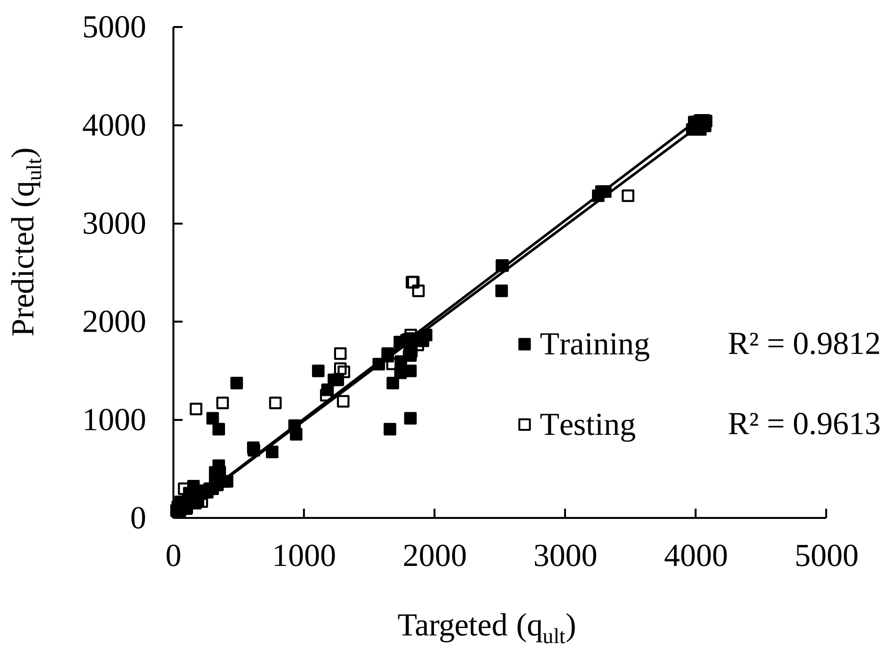


**Fig. 2.** Variation of targeted with the predicted UBC of the footing resting on layered soil using RFR.

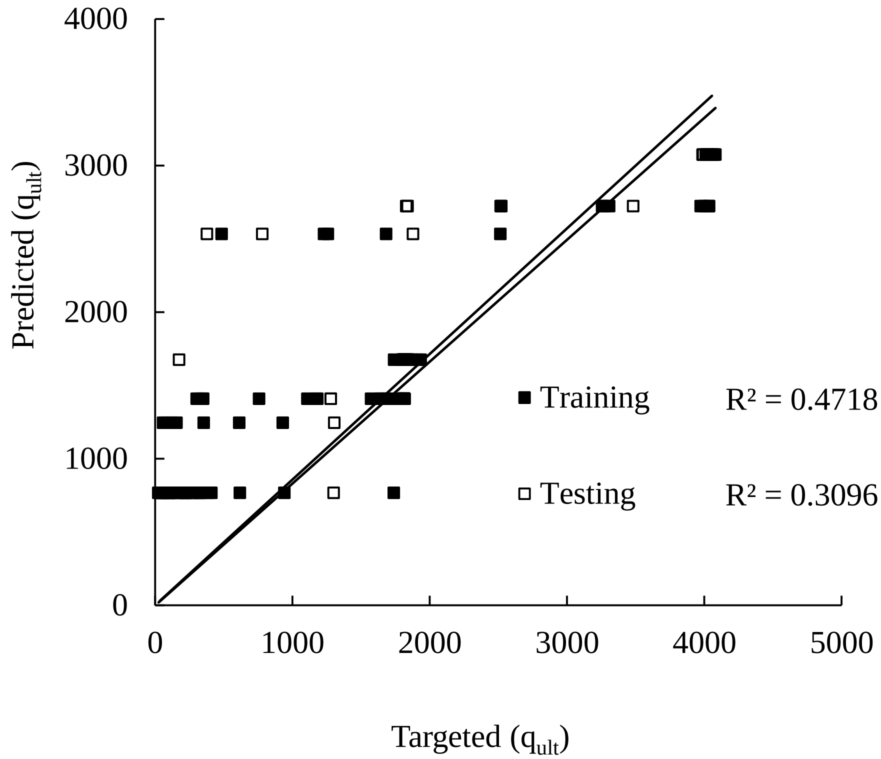


**Fig. 3.** Variation of targeted with the predicted UBC of the footing resting on layered soil using *M5P*.

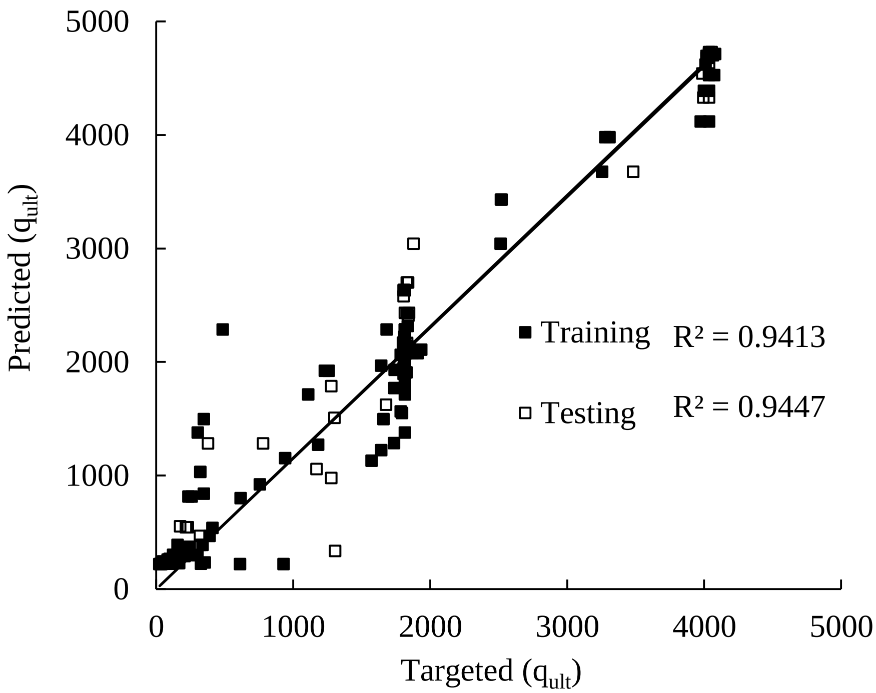


**Fig. 4.** Variation of targeted with the predicted UBC of the footing resting on layered soil using ANN.

The study of the Figs. 2-4 and Table 3 reveals that the RFR shows a better performance in terms of all the performance measures considered in this study. The results of the performance measures of the RFR specifies that this technique can be used to accurately predict the UBC of the strip footing resting on layered soil. The order of prediction of the UBC of the strip footing resting on layered soil was *RFR* followed by *ANN* and the *M5P* technique.

## 6. Sensitivity analysis

Sensitivity analysis has been performed to study the major input parameter affecting the UBC of the strip footing resting on layered soil for the RFR technique. For this, different combination of the input parameters was used. For each of the combination, one of the input parameter was removed and the RFR was carried out in order to check the influence of this omitted input parameter on the output. Further, for each of the combination of the input parameters, the performance measures ($R^2$, *r, MAE, RMSE, MAE* and *RRSE*) were calculated and tabulated in Table 5.

**Table 5**
Sensitivity analysis using RFR.

| Input combinations | Input parameter removed | Random forest regression | | | | | |
|---|---|---|---|---|---|---|---|
| | | $R^2$ | r | MAE | RMSE | RAE | RRSE |
| $\phi_1$, $\phi_2$, $\gamma_1$, $\gamma_2$, *H/B, D/B* and *(H+D)/B* | -- | 0.98 | 0.99 | 70.61 | 168.18 | 7.84 | 13.51 |
| $\phi_2$, $\gamma_1$, $\gamma_2$, *H/B, D/B* and *(H+D)/B* | $\phi_1$ | 0.98 | 0.99 | 69.98 | 166.86 | 7.77 | 13.40 |
| $\phi_1$, $\gamma_1$, $\gamma_2$, *H/B, D/B* and *(H+D)/B* | $\phi_2$ | 0.96 | 0.97 | 77.53 | 177.33 | 8.60 | 14.24 |
| $\phi_1$, $\phi_2$, $\gamma_2$, *H/B, D/B* and *(H+D)/B* | $\gamma_1$ | 0.98 | 0.99 | 71.75 | 166.08 | 7.96 | 13.34 |
| $\phi_1$, $\phi_2$, $\gamma_1$, *H/B, D/B* and *(H+D)/B* | $\gamma_2$ | 0.95 | 0.96 | 91.13 | 188.40 | 10.11 | 15.13 |
| $\phi_1$, $\phi_2$, $\gamma_1$, $\gamma_2$, *D/B* and *(H+D)/B* | *H/B* | 0.98 | 0.99 | 74.65 | 172.75 | 8.28 | 13.87 |
| $\phi_1$, $\phi_2$, $\gamma_1$, $\gamma_2$, *H/B,* and *(H+D)/B* | *D/B* | 0.98 | 0.99 | 72.88 | 171.13 | 8.09 | 13.74 |
| $\phi_1$, $\phi_2$, $\gamma_1$, $\gamma_1$, *H/B,* and *D/B* | *(H+D)/B* | 0.98 | 0.99 | 74.53 | 172.30 | 8.27 | 13.84 |

The study of the Table 5 reveals that the unit weight of loose sand layer sand ($\gamma_2$) followed by friction angle of loose sand layer sand ($\phi_2$) were having key influence in predicting the UBC of the strip footing resting on layered soil using a RFR in comparison to the other input parameters. While removing the other input parameters in each of the combination (except $\phi_2$ and $\gamma_2$) was not having a major influence on the prediction of UBC of the strip footing resting on layered soil using RFR. The results further suggested that the RFR provides the best performance with the data combination involved in the remaining input parameters. This was attributed to the fact that the loose sand layer properties were playing a major role in predicting the UBC of the strip footing resting on layered soil.

## 7. Conclusions

This paper investigates the potential of RFR technique in predicting and identifying the useful parameters affecting the prediction of the UBC of strip footing resting on layered soil using the experimental and theoretical data reported in literature. Based on the results and discussion presented, the following conclusions are put forward.

1. Random forest regression algorithm works well in predicting the ultimate bearing capacity of the strip footing resting on dense sand overlying loose sand deposit in comparison to the *M5P* and the artificial neural network.
2. The order of prediction of the ultimate bearing capacity of the strip footing resting on dense sand overlying loose sand deposit accurately were *RFR* followed by *ANN* and the *M5P* technique.
3. Random forest regression algorithm can effectively be used to identify the useful input parameters affecting ultimate bearing capacity of the strip footing resting on dense sand overlying loose sand deposit.
4. The unit weight and the friction angle of the loose sand layer were playing a major role in predicting the ultimate bearing capacity of strip footing resting on dense sand overlying loose sand deposit.

## Notations

| | |
|---|---|
| ANN | Artificial Neural Network |
| RFR | Random forest regression |
| $\phi_1$ | Friction angle of the dense sand layer |
| $\phi_2$ | Friction angle of the loose sand layer |
| $\gamma_1$ | Unit weight of the dense sand layer |
| $\gamma_2$ | Unit weight of the loose sand layer |
| $H$ | Thickness of the dense sand layer |
| B | Width of footing |
| $D$ | Depth of the footing |
| $q_{ult}$ | Ultimate bearing capacity |
| RMSE | Root Mean Square Error |
| MAE | Mean Absolute Error |
| MAPE | Mean Absolute Percentage Error |
| *RAE* | Root mean square error |
| *RRSE* | Root relative square error |
| $R^2$ | Coefficient Of Determination |
| r | Correlation Coefficient |
| N | Set of the data records that reach the node |
| $N_i$ | Sets resulted from splitting the node according to a given attribute |
| sd | standard deviation |
| F' | Predicted value passed on to the following higher node |
| c | Predicted passed to the current node from lower node |
| b | Estimated value using the technique at this node |
| i | Number of training examples that reach the node below |
| j | Constant |
| k | Numbers of trees developed |
| m | number of variables required to create a tree at each node |

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