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Application of Soft Computing Techniques in Predicting the Ultimate Bearing Capacity of Strip Footing Subjected to Eccentric Inclined Load and Resting on Sand

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ABSTRACT

The present study attempts to predict the ultimate bearing capacity (*UBC*) of the strip footing resting on sand and subjected to inclined load having eccentricity with respect to the vertical using three different soft computing techniques such as support vector mechanism with radial basis function (SVM RBF kernel), M5P model tree (M5P) and random forest regression (RFR). The *UBC* was computed in the form of reduction factor and this reduction factor was assumed to be dependent on the ultimate bearing capacity (q_u) of the strip footing subjected to vertical load, eccentricity ratio (e/B), inclination ratio (α/ϕ) and the embedment ratio (D_f/B). The performance of each model was analyzed by comparing the statistical performance measure parameters. The outcome of present study suggests that SVM RBF kernel predicts the reduction factor with least error followed by M5P and RFR. All the model predictions further outperformed those based on semi-empirical approach available in literature. Finally, sensitivity analysis performed for the SVM RBF kernel model which suggests that the inclination ratio (α/ϕ) and eccentricity ratio (e/B) was an important parameter, in comparison to other parameters, considered for predicting the reduction factor.

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1. Introduction

Estimating the ultimate bearing capacity (*UBC*) of the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand has been a subject of focus for the researchers. The *UBC* in such cases was usually determined in terms of some reduction factor [1]. It was further reported by Patra et al [1] that the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand was primarily governed by the ultimate bearing capacity (q_u) of the strip footing subjected to vertical load, eccentricity ratio (e/B), inclination ratio (α/ϕ) and the embedment ratio (D_f/B). At present, researchers have to evaluate the *UBC* of the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand using semi-empirical and experimental methods. In order to reduce the physical work involved in the experimentation, it is always better to have some kind of mathematical model where major parameters can be calibrated to fit the experimental result in order to understand the relationship among the participating parameters as reported in Dutta et al [2]. In this context, the soft computing techniques such as SVM RBF kernel, M5P and RFR hold promise and can be a suitable choice to predict the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand. The paper presents the application of SVM RBF kernel, M5P and RFR in predicting the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand. The comparison of the performance of the SVM RBF kernel, M5P and RFR with the model reported in literature was also attempted. Finally the sensitivity analysis was performed for the better model obtained in this study.

2. Background

Experimental, numerical, and theoretical studies of the bearing capacity of the footing subjected to inclined load having eccentricity with respect to the vertical have been reported by many researchers [3–6] in the past. For instance, the bearing capacity of strip and circular footing on undrained clay subjected eccentric loading was investigated by Taiebat and Carter [3] with the use of finite element method. Whereas the bearing capacity of strip footing in frictional soil obeying Mohr-Coloumb's failure criteria and subjected to inclined and eccentric loading was explored by Loukidis et al [4] by using finite element method. The obtained results by Loukidis et al [4] suggested that the bearing capacity of the inclined footing was primarily dependent on the friction angle of soil. With the use of limit equilibrium methodology and use of predefined failure surface, Meyerhof [5] and Prakash and Saran [6] developed analytical expressions for computing bearing capacity factor N_c, N_q and N_γ for eccentric inclined footing. Footings resting on layered soils and subjected to inclined load were also researched [7–9] in literature. The semi-empirical equation based on the experimental data for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand was reported by different researchers [1,10,11]. Recently researchers were focusing on the application of soft computing techniques such as ANN, SVM RBF kernel, RFR and M5P in geotechnical engineering [12–21]. In the present study the SVM RBF kernel, M5P and RFR were used, in order to predict the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand.

3. Problem statement

The eccentrically inclined loads on the footings falls under two cases. The first one was known as compensated case and the other one was known as reinforced case as reported by Perloff and Barren [22]. Both the cases were shown in Fig. 1. The footing (having width B) shown in Fig. 1 was subjected to unit ultimate load (L_u) at an eccentricity of e. This unit ultimate load was inclined to the vertical at an angle (α). Experimental data based on the reinforced case type of inclined load having eccentricity with respect to the vertical and acting on the strip footing and reported by Patra et al [1] was used for modelling using soft computing techniques such as SVM RBF kernel, M5P and RFR.

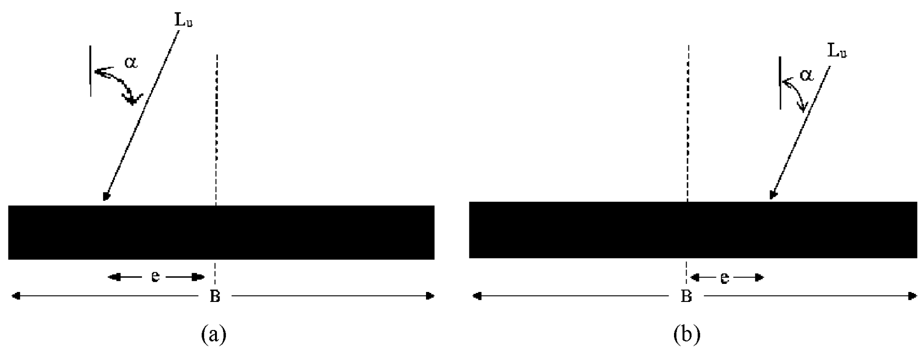


Fig. 1. Strip footing subjected to inclined load having eccentricity with respect to the vertical (a) compensated case and (b) reinforced case.

4. Soft computing techniques

4.1. SVM RBF kernel

Support vector machines were the regression and the classification technique. Principles of optimal separation of the classes were used by these methods. For the classes that can be separated, it chooses the linear classifier from among the many of such classifiers. The chosen classifiers should have the ability of having an upper bound or minimizing the generalization error. This can be arrived at using risk minimization. The hyperplane selected would thereby leave the largest margin between the two classes. For the classes that cannot be separated, the hyperplane which minimizes and maximizes a quantity proportional to the number of misclassified errors and the margin respectively was selected. However, one has to choose in advance, a positive constant that controls the balance between the margin and the misclassified error. The non-linear decision surfaces were handled by projecting the actual set of parameters onto a higher dimensional feature space. The problem was then formulated as a linear classification problem in this feature space. Insensitive loss function as an alternative was proposed in the support vector regression by Vapnik [23]. The objective of this proposed insensitive loss function was to find the largest deviation from the actual target vector for the training data. At the same time, this proposed insensitive loss function has to be as flat as possible [24]. A concept of kernel function was proposed by Vapnik [23] for the non-linear support vector regression. In support vector regression, few parameters that control the complexity of prediction have to be user-defined like the kernel and the kernel specific parameters, optimization of the regularization parameter C and the size of error in sensitive zone need to be determined. The optimization algorithm of support vector regression helps us in solving a linearly constrained quadratic programming function leading to a unique, optimal and global solution.

4.2. M5P model tree

M5P was a conventional decision tree. This tree was constructed using divide-and-conquer technique. This technique has been in use for the prediction of continuous numeric parameters. These numeric parameters have a linear function at the terminal node. The tree generation was done in two steps. In the first step, a splitting criterion was adopted to create a decision tree. The standard deviation of the class values was the basis of this splitting criterion. This standard deviation reaches the node as a measure of the error at that node and calculates the expected reduction in the error. In order to make the node more pure, splitting process forces the child node to have smaller value of the standard deviation as compared to the parent node. After examining all the possible splits and to maximize the expected error reduction, M5 model tree chooses the split. The data division produces a large tree which may cause over fitting of the testing data. To remove the problem of the over fitting, it was suggested by Quinlin [25] to use a pruning method to prune back the over grown tree which was achieved by replacing a sub tree with a linear regression function in the second step.

4.3. Random forest regression

Random forest was a classification and regression method consisting of a combination of tree predictors. To generate each tree, the random vector sample was taken independently from the input vector. In regression, numerical values as opposed to class labels, which were used by the random forest classifier was taken by the tree predictor [26]. In order to grow a tree, RFR at each node, uses a combination of parameters or selected parameter (chosen randomly). Bagging technique (a technique where the data were randomly drawn and replaced with from the original data reserved for training) was used to generate the training data. Breiman [27] reported that the training data can also randomly be selected for constructing an individual tree for each of the feature combination. 67 % of the original data was used for the training and the remaining data was left out from every tree grown in bagging. A variable selection procedure as well as pruning method was required to design a tree predictor. Selections of variable for the tree induction, number of approaches (information gain ratio criterion [25] and Gini index [28]) were available and used for the parameter selection measures in the tree induction. In this study, gini index was used as a parameter selection measure in the RFR approach which measures the impurity of a parameter with respect to the output. The tree was allowed to grow to the maximum depth of the training data with the use of combination of variables. Further, the fully grown trees were not allowed to be pruned back in this approach. This was a major advantage of RFR over the tree methods (M5P). As suggested by Breiman [26] as the numbers of tree increases, the generalization error converges even if pruning of the tree was not done and hence the overfitting of the data was not a problem [29]. Two of the user defined parameters required for the RFR was numbers of trees to be developed (designated as k) and number of variables required to create a tree at each node (designated as m) as reported by Breiman [26]. At each node, through best split, selected variables were searched. Thus, RFR contains two user defined parameters (k and m) and these parameters can have any value. A numerical value is thus obtained from the RFR as an output. Hence it is possible to calculate the mean square error for the numerical predictor. Further, random forest predictor was formed by considering the average of the error over k number of trees.

5. Data, performance measures and user defined parameters

SVM RBF kernel, M5P and RFR based soft computing models were developed using a wide range of data comprising 120 experimental data reported in literature by Patra et al [1]. This data contains 60 records on the dense sand and the remaining data record was on the medium dense sand. Two parts of the total data records were made. The first part contains of 84 data which were used for the training purpose. The second part of the data was used for the testing purpose. The data for the training and the testing purpose were selected randomly. It is worth mentioning here that the total data for the training and the testing was divided based on the rules reported [20,21]. The parameters used as an input for modelling were eccentricity ratio (e/B), inclination ratio (α/ϕ), embedment ratio (D_f/B) and the ultimate bearing capacity (q_u) of the strip footing subjected to vertical load. The output was the reduction factor (RF, ratio of ultimate bearing capacity with eccentricity ratio (e/B) and inclination ratio (α/ϕ) at an embedment ratio (D_f/B) *to the ultimate bearing capacity* with centric vertical loading ($e/B = 0$ and $\alpha/\phi = 0$) at an embedment ratio (D_f/B)). Range of parameters considered for modelling was tabulated in Table 1. The prediction accuracy for the various soft computing techniques such as SVM RBF kernel, M5P and RFR were assessed through various performance measures such as r, R^2, *MSE, RMSE, MAE* and *MAPE*. Performance measures such as coefficient of determination (R^2) and coefficient of correlation (r) close to 1 and 0 indicating a best and poor fit respectively whereas other performance measures (*MSE, RMSE, MAE* and *MAPE*) has to be minimum at the same time for the model under consideration.

Table 1
Range of data used for the training and testing.

Input & output parameters	Train data set				Test data set			
	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
D_f/B	0	1	0.5	0.41	0	1	0.5	0.41
α/ϕ	0	0.53	0.25	0.18	0	0.53	0.26	0.19
e/B	0	0.15	0.07	0.06	0	0.15	0.08	0.05
q_u (kN/m^2)	16.68	353.16	120.41	74.86	13.34	278.6	116.54	70.92
RF	0.14	1	0.56	0.22	0.13	1	0.55	0.21

Lesser the *MSE, RMSE, MAE* and *MAPE*, better is the model under consideration to predict the output. Performance measures were compared for each of the trial in order to fix the optimal values of the user defined parameters. The user defined parameters finally obtained for the SVM RBF kernel, M5P and RFR were tabulated in the Table 2.

Table 2
Optimal values of user defined parameters for the different soft computing techniques.

Classifiers used	User defined parameters
SVM RBF kernel	$C= 1.6$, $\gamma= 3$
M5P	M=5
RFR	k=2, m=1, I=100

6. Results and discussions

The performance measures (r, R^2, *MSE, RMSE, MAE* and *MAPE*) for the SVM RBF kernel, M5P and RFR in the training and the testing phases were calculated and were shown in Figs. 2 and 3 respectively.

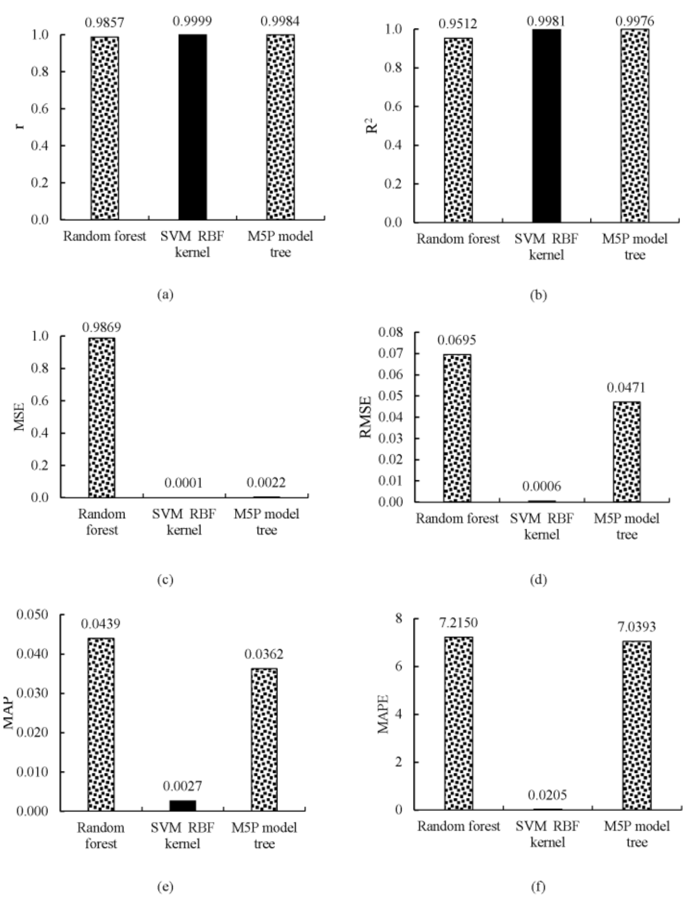


Fig. 2. Performance measures for different soft computing techniques for the training dataset.

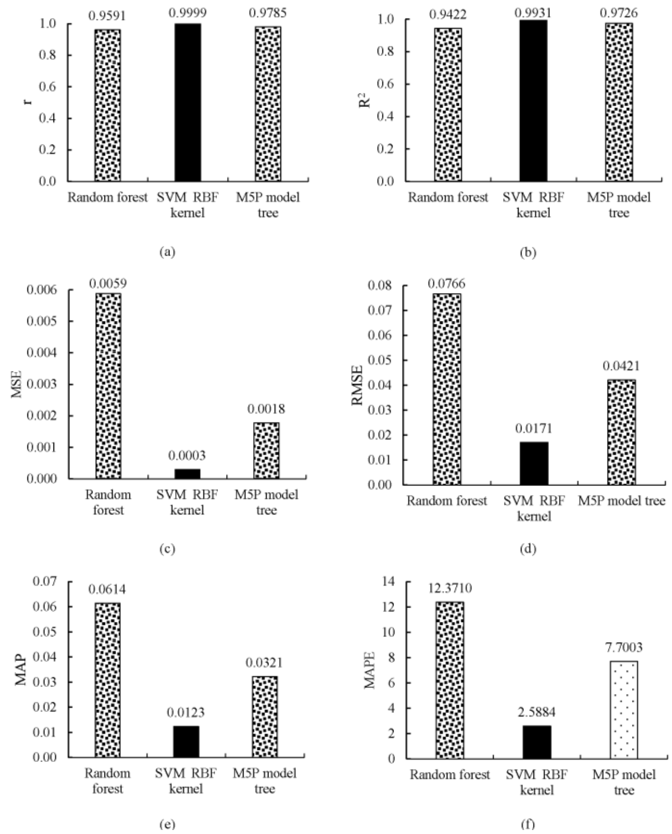


Fig. 3. Performance measures for different soft computing techniques for the testing dataset.

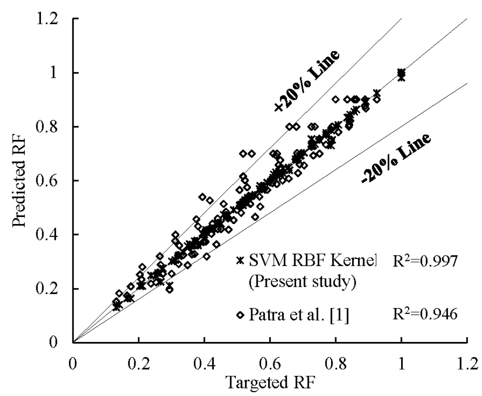
Model showing superior values of the performance measures (*r, R^2, MSE, RMSE, MAE* and *MAPE*) was shown in dark black colour in order to differentiate it with respect to other models in Figs. 2 and 3. Study of Fig. 2 reveals that the coefficient of determination (R^2), correlation coefficient (r), *MSE, RMSE, MAE* and *MAPE* observed for all the three models were in the range of 0.9857 to 0.9999, 0.9512 to 0.9981, 0.0001 to 0.9869, 0.0006 to 0.0695, 0.0027 to 0.0439 and 0.0205 to 7.2150 respectively for the training data. These performance measures were in the range of 0.9591 to 0.9999, 0.9422 to 0.9726, 0.0003 to 0.0059, 0.0171 to 0.0766, 0.0123 to 0.0614 and 2.5884 to 12.3710 respectively for the testing data as evident from Fig. 3. If the performance measure (r and R^2) for any model was closer to 1 and the values of the other performance measures (*MSE, RMSE, MAE* and *MAPE*) were at the minimum, it represents a strong correlation exists between the predicted and the experimental values as reported by Dutta et al [2]. From the study of Figs. 2 and 3, and following [2], one can notice that the developed SVM RBF kernel model can be considered as the best model followed by M5P and the RFR model in this order as the r and R^2 was highest for the SVM RBF kernel model and other performance measures (*MSE, RMSE, MAE* and *MAPE*) were the least in comparison to M5P and the RFR model.

6.1. Comparison with literature

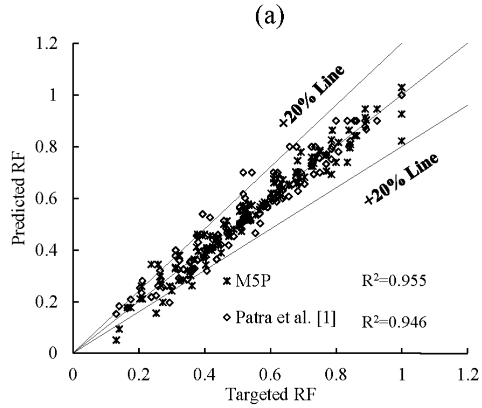
The reduction factor obtained from the developed SVM RBF kernel, M5P and the RFR model were compared with the reduction factor equation developed from the laboratory experimental data and reported by Patra et al [1] which can be written as

$$RF = \left[1 - 2\left(\frac{e}{B}\right)\right]\left[1 - \frac{\alpha}{\phi}\right]^{\left(1.5 - 0.7\frac{D_f}{B}\right)} \tag{1}$$

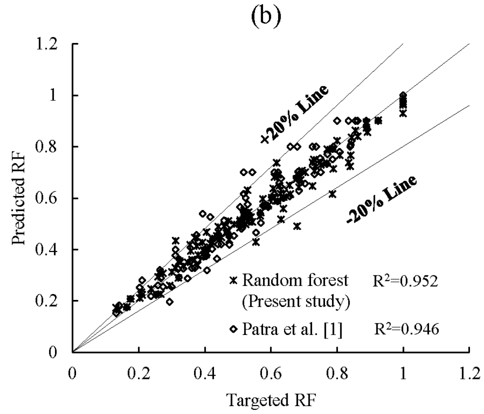
The comparison of the SVM RBF kernel, M5P and the RFR models with the one reported in the literature was shown Figs. 4(a-c). The study of the Fig. 4 (a-c) reveals that, the majority of the predicted values using SVM RBF kernel, M5P and the RFR models were lying within the range of ±20% lines resulting higher values of r & R^2 and lower values of *MSE, RMSE, MAE* & *MAPE* for the SVM RBF kernel, M5P and the RFR models in comparison to the equation reported by Patra et al [1].



(a)



(b)



(c)

Fig. 4. Comparison of actual versus predicted reduction factor for (a) SVM RBF kernel and literature (b) M5P and literature (c) RFR and literature.

Further, a close examination of Fig. 4 (a) reveals that, the values obtained from the SVM RBF kernel model falls inside the ±20% lines in comparison to the values obtained from [1] equation. Few of the values obtained from random forest regression, M5P and the equation reported by Patra et al [1] falls outside the ±20% lines as evident from Figs. 4 (b) and (c). A careful study of the Fig. 4(a-c) reveals that, the R^2 for the SVM RBF kernel, M5P, RFR, and the equation reported by Patra et al [1] was 0.997, 0.955, 0.952 and 0.946 respectively. This indicates that the prediction using SVM RBF kernel, M5P and RFR were superior to the equation reported by Patra et al [1] for the selected range of the parameters. However, with the consideration of other errors (*MSE, RMSE, MAE* and *MAPE*), SVM RBF kernel can be considered as best among the selected models. With the use of SVM RBF kernel model the maximum and average deviation with respect to experimental values was about 28.23 and 0.62 respectively, which is acceptable. Further, comparison of the predicted reduction factor obtained from the SVM RBF kernel model were also made with the equations reported in literature [4,5,30,31].

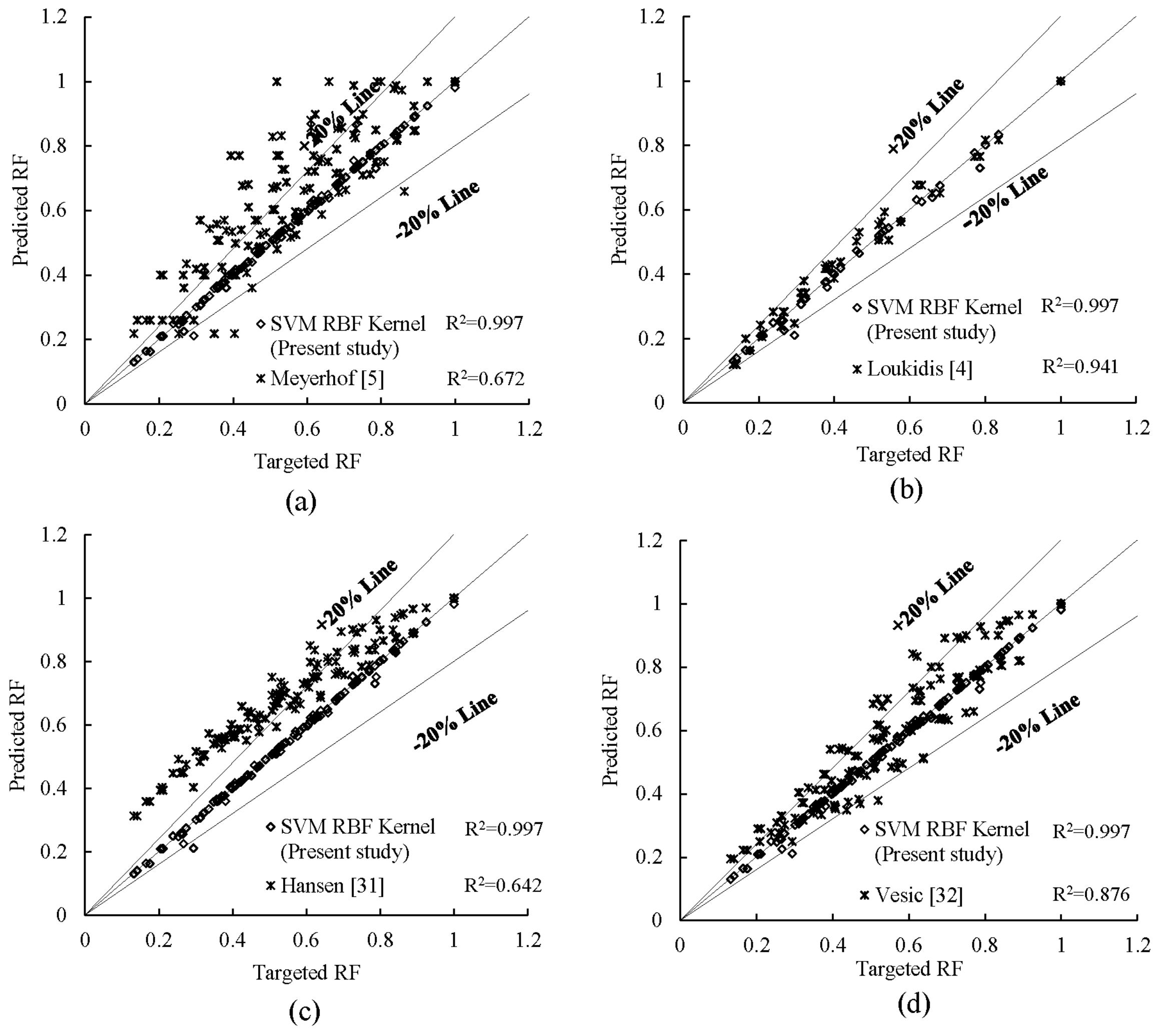


Fig. 5. Comparison of actual versus predicted reduction factor using SVM RBF kernel with (a) Meyerhof [5] (b) Loukidis [4] (c) Hansen [31] (d) Vesic [32].

The results of this study are shown in Figs. 5 (a) to (d). Study of the Fig. 5 reveals that the prediction of reduction factor using SVM RBF kernel model was superior to the one obtained from the equation reported by [4,5,30,31]. It is pertinent to mention here that the equation proposed by the [4] was having a limitation as it was applicable for the surface footings only. Hence the surface footing data was used to compare the prediction in Fig. 5b. Whereas, the equations [5,30,31] proposed were for the embedded footing subjected to eccentric inclined load. The ultimate bearing capacity was determined using effective width (B'=B-2e) in the equation reported by [5] and the same effective width was used in the shape and the depth factor calculation. Similarly, for the equations reported in [4,30,31], the above procedure was followed. The R^2 obtained from the equations of [4,5,30,31] were 0.941, 0.672, 0.642 and 0.876 respectively whereas the R^2 obtained from the SVM RBF kernel model was 0.997 indicating its superiority in predicting the reduction factor. Further, the distinction of the SVM RBF kernel model for determining the reduction factor lies in its powerful ability to model the behaviour without requesting a prior form of the existing relationships.

7. Sensitivity analysis

In order to study the major input parameters affecting the output reduction factor, a sensitivity analysis was performed. For this purpose, different combination of the input parameters was used. For every combination, one of the input parameter was removed and the effect of this removed parameter on the output reduction factor was measured in terms of performance measures (r, R^2, *MSE, RMSE, MAE* & *MAPE*) for the SVM RBF kernel model and the calculated values of these performance measures were tabulated in Table 3 for different combination of the input parameters.

Table 3
Sensitivity analysis for the SVM RBF kernel model.

Input combinations	Input parameter removed	SVM RBF kernel					
		r	R^2	*MSE*	*RMSE*	*MAE*	*MAPE*
D_f/B, α/ϕ, e/B, q_u (kN/m^2)	--	0.9999	0.9931	0.0003	0.0171	0.0123	2.5884
α/ϕ, e/B, q_u (kN/m^2)	D_f/B	0.9987	0.9586	0.0018	0.0425	0.0230	5.4369
D_f/B,, e/B, q_u (kN/m^2)	α/ϕ	0.9140	0.7238	0.0090	0.0951	0.0616	12.5483
D_f/B, α/ϕ, q_u (kN/m2)	e/B	0.9615	0.8612	0.0054	0.0738	0.0442	8.7916
D_f/B, α/ϕ, e/B	q_u	0.9989	0.9956	0.0002	0.0136	0.0067	1.2257

Study of the Table 3 reveals that the inclination ratio (α/ϕ) followed by *UBC* of the strip footing subjected to vertical load and eccentricity ratio were having the key influence in the prediction of the reduction factor of the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand using a SVM RBF kernel model in comparison to the other input parameters. Removing the other input parameters in each of the combination (except α/ϕ and e/B) was not having a major influence on the prediction of reduction factor of the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand using SVM RBF kernel model. The results further suggested that the SVM RBF kernel provides the best performance with the data combination involved in the remaining input parameters. This was attributed to the fact that the eccentricity ratio was playing a major role in predicting the reduction factor.

8. Conclusions

This paper investigates the application of SVM RBF kernel, M5P and the RFR technique in predicting and identifying the useful parameters affecting the prediction of the reduction factor using the experimental data reported in literature. Based on the results and discussion presented, the following conclusions were drawn.

1. SVM RBF kernel works well in predicting the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand in comparison to the M5P and the RFR.
2. The order of prediction of the reduction factor for the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand were SVM RBF kernel followed by M5P model tree and random forest regression.
3. The R^2 for the SVM RBF kernel, M5P, RFR, and the equation reported in literature was 0.997, 0.955, 0.952 and 0.946 respectively.
4. SVM RBF kernel can effectively be used to identify the useful input parameters affecting reduction factor of the strip footing subjected to inclined load having eccentricity with respect to the vertical and resting on sand.
5. The major role in predicting the reduction factor was played by inclination ratio (α/ϕ) followed by eccentricity ratio (e/B). The contribution by other parameters such as ultimate bearing capacity (q_u) of the strip footing subjected to vertical load and (embedment depth (D_f/B) was marginal.

Notations

RFR	Random forest regression
SVM RBF kernel	Support vector machines RBF kernel
M5P	M5P model tree
L_u	Unit ultimate load on the footing
e	eccentricity
α	load inclination
B	Width of the footing
B'	Effective width of the footing
D_f/B	Embedment ratio
α/ϕ	Inclination ratio
e/B	Eccentricity ratio
q_u	Ultimate bearing capacity
RF	Reduction factor
r	Correlation Coefficient

R^2	Coefficient of Determination
MSE	Mean square error
RMSE	Root mean square error
MAE	Mean absolute error
MAPE	Mean absolute percentage error
k	The number of trees
m	The number of parameters to grow individual trees
C, γ, M, k and I	User defined parameters

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