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Soft Computing Based Prediction of Unconfined Compressive Strength of Fly Ash Stabilised Organic Clay

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ABSTRACT

The current study uses machine learning techniques such as Random Forest Regression (RFR), Artificial Neural Networks (ANN), Support Vector Machines Ploy kernel (SVMP), Support Vector Machines Radial Basis Function Kernel (SVMRBK), and M5P model tree (M5P) to estimate unconfined compressive strength of organic clay stabilized with fly ash. The unconfined compressive strength of stabilized clay was computed by considering the different input variables namely i) the ratio of Cao to Sio_2, ii) organic content (OC), iii) fly ash (FA_{per}) content, iv) the unconfined compressive strength of organic clay without fly ash (UCS_0) and v) the pH of soil-fly ash (pH_{mix}). By comparing the performance measure parameters, each model performance is evaluated. The result of present study can conclude the random forest regression (RFR) model predicts the unconfined compressive strength of the organic clay stabilized with fly ash with least error followed by Support Vector Machines Radial Basis Function Kernel (SVMRBK), Support Vector Machines Ploy kernel (SVMP), Artificial Neural Networks (ANN) and M5P model tree (M5P). When compared to the semi-empirical model available in the literature, all of the model predictions given in this study perform well. Finally, the RFR and SVMRBK sensitivity analyses revealed that the CaO/SiO_2 ratio was the most relevant parameter in the prediction of unconfined compressive strength.

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1. Introduction

Organic soils' poor shear strength and high compressibility make road and rail building difficult [1]. Several experiments [2,3] have been undertaken to increase organic clay soil shear capacity and improve compressibility. This research involves time-consuming, cumbersome experimentation. Soft computing techniques, which use prior data for prediction, show promise. Soft computing techniques have been successfully implemented for geotechnical applications involving the prediction of soil properties such as the specific surface of fine grained [4], cation exchange capacity, water percentage at field capacity and permanent wilting point [5], permeability coefficient with various permeability test data [6], dry unit weight of soils measured in the form of water contents and P-wave velocities of compacted soils [7], using t-SNE. These approaches also accurately predicted the swell potential of different soils [8] and retaining wall swelling pressure [9]. These techniques were also used to estimate sand shear strength [10–12], to determine the bearing capacity and settlement of shallow footings [13–20], pile capacity [21,22], to estimate the compressive strength of concrete [23], analyze the behaviour of a steel 1-panel shear wall under explosive loads [24], predict the magnitude of an earthquake along the Zagros fault using time series and an ensemble model [25], predict the nonlinear seismic response approximation of steel moment frames [26], and estimate seismic retrofit cost using structural parameters [27]. Fly ash has been introduced for use with and without cement in the field of soil stabilization to improve the strength of the soil. Several prior research [28–35] have attempted to determine the appropriate amount of fly ash to be employed, with the relevance of the strength prediction. According to the existing literature, the novelty of this work resides in the fact that no other work has used soft computing techniques to forecast the unconfined compressive strength of fly ash-stabilized organic clay. This research proposes the use of soft computing techniques to forecast the unconfined compressive strength of organic clay stabilized with fly ash to fill this void. When developing the models, the following objectives were considered.

i. Determining the parameters that affect the unconfined compressive strength of fly ash stabilized organic clay and analyzing the correlations between these parameters.
ii. To construct a soft computing model for forecasting the unconfined compressive strength of fly ash-stabilized organic clay and to evaluate the model's accuracy using statistical parameters.
iii. To develop an empirical model using a soft computing strategy to forecast the unconfined compressive strength of fly ash-stabilized organic clay.
iv. To perform the sensitivity analysis on the best performing model based on statistical parameters.
v. To compare the accuracy of the generated model's prediction of the unconfined compressive strength of fly ash-stabilized organic clay with available experimental research.

The ratio of Cao to Sio_2, fly ash (FA_{per}) content, organic content (OC), pH of soil-fly ash (pH_{mix}) and the unconfined compressive strength of organic clay without fly ash (UCS_0) were all employed as input variables.

2. Soft computing techniques

Four soft computing techniques have been used to predict the unconfined compressive strength of fly ash-stabilized organic clay. The various soft computing techniques used were artificial neural network (A.N.N), random forest regression (R.F.R), support vector mechanism (S.V.M) and M5P model tree (M5P). Among all the above techniques, ANN is a more trustworthy and exact alternative to regression-based approaches and formulas. This is because this modelling approach lacks a formal expression between input and output variables. ANN requires a lengthy trial-and-error approach to identify network characteristics such as hidden layers and neurons. Neural networks demand more data than the average person has. Decision tree approach (M5P) generates linear input-output linkages. Transforming the dataset into a different domain might create nonlinear relationships using decision tree methods. Random forest training is cheaper and doesn't require GPUs. Random forests offer an efficient alternative to decision trees. SVMs with non-linear kernels don't need to confine network size and layer count. Parameters increase with the amount of support vectors used. SVM may need hundreds of support vectors when working with text data. Each model has advantages and downsides, as discussed above. The various soft computing techniques used in this investigation are presented in the following sections.

2.1. Artificial neural networks

Neural networks can tackle complex non-linear problems for general use. Structure-based weighted linkages connect simple processing units in the network. Bishop [36] said that these networks will learn by adjusting their link weights. Back-propagation neural networks have processing nodes. Every processing node acts like a neuron and has two purposes. All inputs are added and sent through an activation function (any differentiable function) to generate output. Each layer's working nodes are fully linked to the next layer and interrelated. In a back-propagation algorithm, the input layer distributes network data. Hidden layers are behind-the-input-layer processing layers. Last treatment layer is output. Network determines connection weights. Initial weights are random. Several techniques that alter interconnection weights can minimize training error in multi-layer networks [36]. Feed-forward back-propagation is a popular strategy. An iterative approach is used to minimize an error function spanning system output and target outputs from the training set. Training reduces the disparity between the network's current and desired outputs. The network passes training data to output units. Existing and desired target values differ, causing a network issue. The weights linking the units are modified based on error magnitude, and the defect is passed back to the input layer. The technique is repeated until the error value is optimal or a given number of times.

2.2. Random forest regression

Random forest is a tree-based classification and regression method. R.F.R.'s trees were produced using random vectors. Using the input vector, this random vector was created. The tree predictor employs numbers instead of class labels[37]. At each node in this study's R.F.R., a random variable or permutation is used. These criteria were chosen for tree growth. The training data was prepared through bagging, which involves randomly choosing data and replacing it with training-only data. For each of the feature combinations presented, the training data can alternatively be chosen at random for the development of an individual tree [38]. In this study, 70% of the inputs were randomly picked for training, while the remaining one-third was eliminated from each tree. A tree predictor must use pruning and variable hiring. Literature described many ways [39,40]. This investigation's R.F.R. method utilizes Gini index variable selection. This variable selection approach evaluates impurity based on ultimate bearing capability. By mixing variables, R.F.R. allows you build a tree to a fresh training data set's deepest point. Full-grown trees weren't pruned. It was stated by [38] that this provides R.F.R. an edge over M5P. According to [41], tree-based algorithm effectiveness is dictated by pruning techniques, not variable selection. As trees develop, the training error normally fits, unless the tree was trimmed. According to [42], overfitting the datasets is not a problem. Further, [38] reported two R.F.R. parameters such as (i) Number of variables (m) at each node to produce a tree (ii) Number of trees to be grown (k). Each node's optimum split was determined by selecting variables. The R.F.R. consists of k user-grown trees. Because R.F.R.'s output is a number, generalization mistakes like mean square can be determined. The R.F.R. was calculated using the average general error over k decision trees.

2.3. M5P model tree

The M5P model tree was a binary decision tree with a linear regression algorithm at the linear endpoint (leaf) node and predicted continuous valued characteristics. Create tree-based models using divide-and-conquer. Model tree generation requires two steps. First, use a dividing criterion to create a decision tree. The M5P model tree computational uses a breaking centered on the class value's standard error to approach nodes as a measurement of the inaccuracy and compute the expected reduction through this inaccuracy because of assessing individual attribute at a specific node. The division operation makes the child node purer by reducing its standard error. M5P selects the split that minimizes expected error. After separation, a huge tree-like structure results, producing overfitting, which is rectified by trimming. Stage two prunes the overgrowth tree and replaces subtrees with linear regression functions. The model tree approach divides space into regions using linear regression. M5P model tree information was reported by [39].

2.4. Support vector mechanism

Support vector machines (SVM) were created using computational learning theory [43]. This approach separated classes optimally. SVM finds the separable linear classifiers that reduce prediction error. The chosen hyperplane allows the most space between the two groups. When two classes are inseparable, SVM finds the hyperplane that maximizes margin and reduces misclassification errors. A favorable constant should be given in advance to manage these problems. This SVM method can create non-linear decision surfaces. SVM involves projecting response variables into a larger space and generating a linear classification problem. Support Vector Regression was introduced by [43] to find a function with the least deviation from the real objective and to be as flat as possible. He also provided the kernel function as a non-linear SVR with an insensitive loss function. SVR needs fewer user-defined parameters in addition to kernel parameters. Finding the appropriate mix of regularization variable C and critical zone inaccuracy affects forecasting complexity. SVR's key value is its optimization technique, which solves a linearly constrained quadratic programming function to find a novel, optimal, and universal solution.

3. Data, performance measures and user defined parameters

R.F.R., A.N.N., S.V.M.P., S.V.M.R.B.K., and M5P computational intelligence models were created based on a diverse set of data as reported in literature [23]. Researchers [11] and [12] utilised 41 and 60 data sets for artificial neural network (A.N.N.) implementations, respectively. As a result, the datasets used in this investigation was comparable. The data collection comprises 18 datasets for three distinct organic soils: Markey peat, Lawson soil, and Theresa soil. The whole data records were divided into two portions. The very first segment contains 38 records that were utilised as part of the training process. The testing process took up the remainder of the second segment of the data records. The train and test records were chosen at random. It is also important to mention that the entire training and testing data record was separated according to the guidelines set out by [44,45]. The variables utilised as initial input data for simulation are as follows: i) ratio of Cao to Sio_2, ii) organic content (OC), iii) Fly ash (FA_{per}) content, iv) unconfined compressive strength of organic clay without fly ash (UCS_0) and v) pH of soil-fly ash (pH_{mix}). The output was the unconfined compressive strength of stabilized organic clay with fly ash (UCS). It is pertinent to mention here that, the Cao/Sio_2 and fly ash percentage (FA_{per}) were acting a significant role in improving the unconfined compressive strength of organic clay- fly ash mix as reported by [30]. As reported by [30,46] that the organic content and the pH_{max} more than 10 % and 5 % respectively will affect the strength properties of the organic clay-fly ash mix. Hence, organic content (OC) and the pH of the soil-fly ash mix (pH_{mix}) were also included as input parameters as their values were more than 10 % and 5 % in Markey peat, Lawson soil and Theresa soil. The erodibility of treated un-saturated soil using support vector machines based on 121 data set was reported in literature [47]. Table 1 lists the parameters ranges that were used for modelling.

Table 1
Parameters ranges utilised in the training and testing phases.

Input & output parameters	Train data set				Test data set			
	Min	Max	Mean	SD	Min	Max	Mean	SD
Cao/Sio_2	0.09	1.15	0.64	0.41	0.09	1.15	0.66	0.38
OC (%)	5.00	27.00	12.29	10.14	5.00	27.00	13.56	10.76
$FA_{pe}r$ (%)	10.00	30.00	20.00	8.38	10.00	30.00	20.00	8.17
$UCS_{0\ (kPa)}$	15.00	57.00	36.55	17.25	15.00	57.00	34.69	17.93
pH	7.27	11.75	9.66	1.21	763.00	12.10	9.76	1.31
UCS (kPa)	50.85	490.14	201.34	126.37	47.68	428.87	204.96	125.76

Note: Min-Minimum; Max-Maximum; SD-Standard Deviation

Various performance metrics such as coefficient of correlation (r), determination coefficient (R^2), Mean Square Error (M.S.E.), Root Mean Square Error (R.M.S.E.), Mean Absolute Error

(M.A.E.), and Mean Absolute Percentage Error (M.A.P.E.) have been used to evaluate the accuracy rate of various soft computing models such as R.F.R., A.N.N., S.V.M.P., S.V.M.R.B.K., and M5P. The performance metrics (M.S.E., R.M.S.E., M.A.E., and M.A.P.E.) must be minimal at the same time for the model under consideration, whereas determination coefficient (R^2) and coefficient of correlation (r) near to 1 and 0 indicate a best and bad fit, respectively. The lower the M.S.E., R.M.S.E., M.A.E., and M.A.P.E., a higher the quality is in predicting the outputs. For every test, performance metrics were paled in comparison in order to determine the best values for the user-defined variables. Table 2 lists the user-defined variables for the R.F.R., A.N.N., S.V.M.P., S.V.M.R.B.K., and M5P that were eventually obtained.

Table 2
Optimal user-defined variable values for various soft computing approaches.

Classifiers used	User defined variables
R.F.R.	k=2, m=2, I=100
A.N.N.	Learning rate = 0.2, momentum = 0.1, epochs = 500, Hidden layers = 4
S.V.M.P.	d = 3, C = 1.4
S.V.M.R.B.K	γ = 3, C = 1.4
M5P	M = 5

4. Results and discussions

In the training and testing stages, the estimated performance metrics (r, R2, M.S.E., R.M.S.E., M.A.E., and M.A.P.E.) for the R.F.R., A.N.N., S.V.M.P., S.V.M.R.B.K., and M5P were displayed in Fig. 1. To distinguish from other models in Fig. 1, the model with strongly acceptable values of the accuracy testing variables (r, R^2, M.S.E., R.M.S.E., M.A.E., and M.A.P.E.) was represented in dark black colour. The determination coefficient (R^2), coefficient of correlation (r), M.S.E., R.M.S.E., M.A.E., and M.A.P.E. observed for all five models were varied about 0.975 to 0.999, 0.951 to 0.999, 1.72 to 2590.35, 1.31 to 50.90,0.67 to 39.48and 0.46 to 26.60 for such training phase, respectively. These ranges are displayed in the Fig. 1. As shown in Fig. 1, these performance measures for the testing phase varied from 0.933 to 0.999, 0.957 to 0.998, 84.59 to 2464.10, 9.20 to 49.64, 7.87 to 29.47, and 5.18 to 24.75 respectively. According to [12,47], if the accuracy testing variables (r and R^2) for any models was near to 1 while the other accuracy testing variables (M.S.E., R.M.S.E., M.A.E., and M.A.P.E.) were at their lowest, this implies that the expected and observed outcomes are highly correlated. Similar to [12,47], the developed R.F.R. model can be considered the best model, followed by S.V.M.R.B.K., S.V.M.P., A.N.N., and M5P within this sequence, because the R.F.R. model's r and R^2 were the maximum, and other accuracy testing variables (M.S.E., R.M.S.E., M.A.E., and M.A.P.E.) were the lowest in compared to S.V.M.R.B.K., S.V.M.P., A.N.N., and M5P.

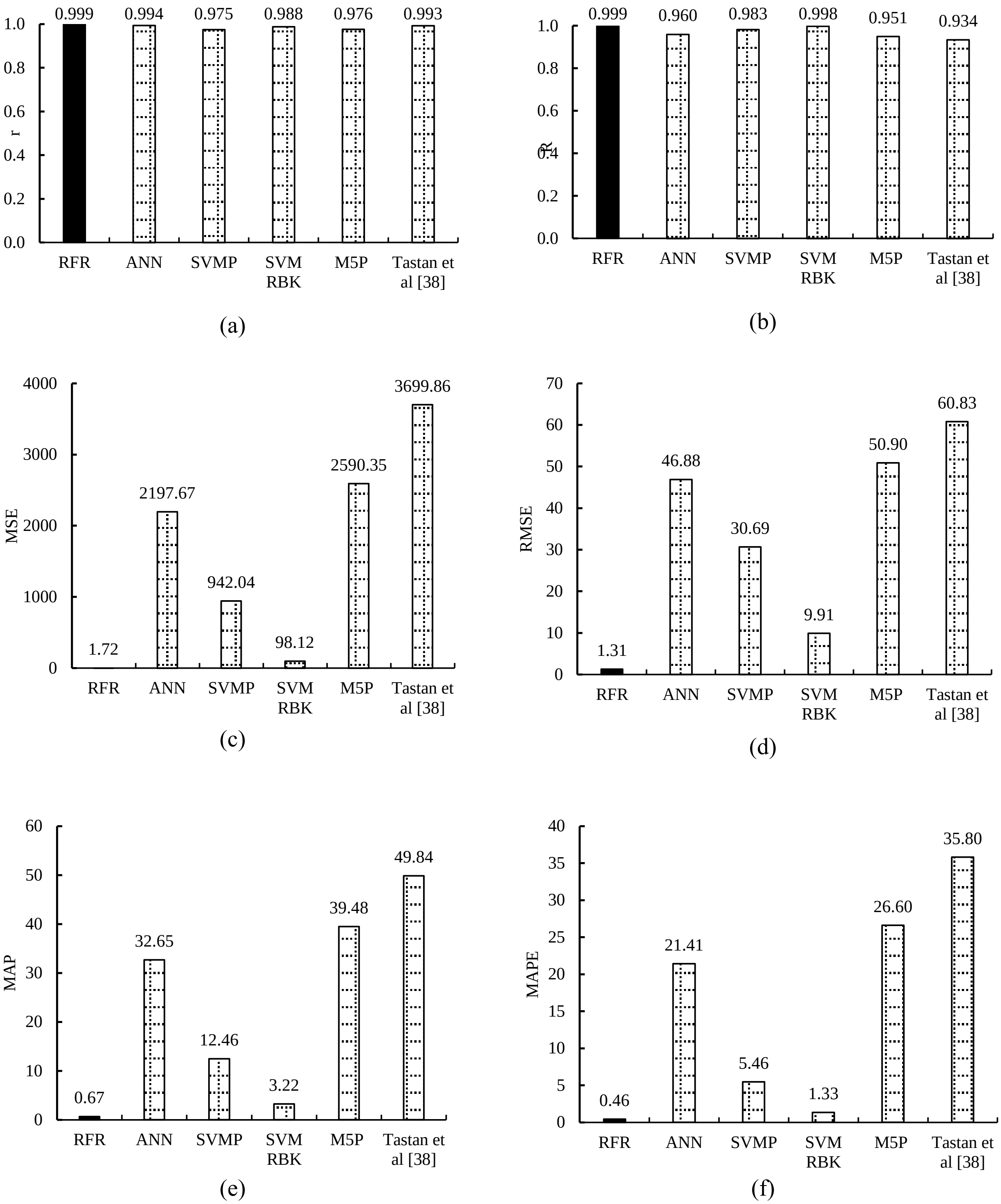

Fig. 1. Variation of performance metrics for different algorithms during the training period.

5. Comparison with literature

An unconfined compressive strength (UCS) equation constructed from research lab experimental observations and presented by [30] was expressed in below equation (1). The R.F.R., A.N.N., S.V.M.R.B.K., S.V.M.P., and M5P findings were compared with the equation (1) result.

$$UCS = -320 + 795\left(\frac{Cao}{Sio_2}\right) - 573\left(\frac{Cao}{Sio_2}\right)^2 - 125{,}673\left(e^{-OC}\right) + 6\left(FA_{per}\right) + 25\left(UCS_0\right) - 33\left(pH_{mix}\right) \tag{1}$$

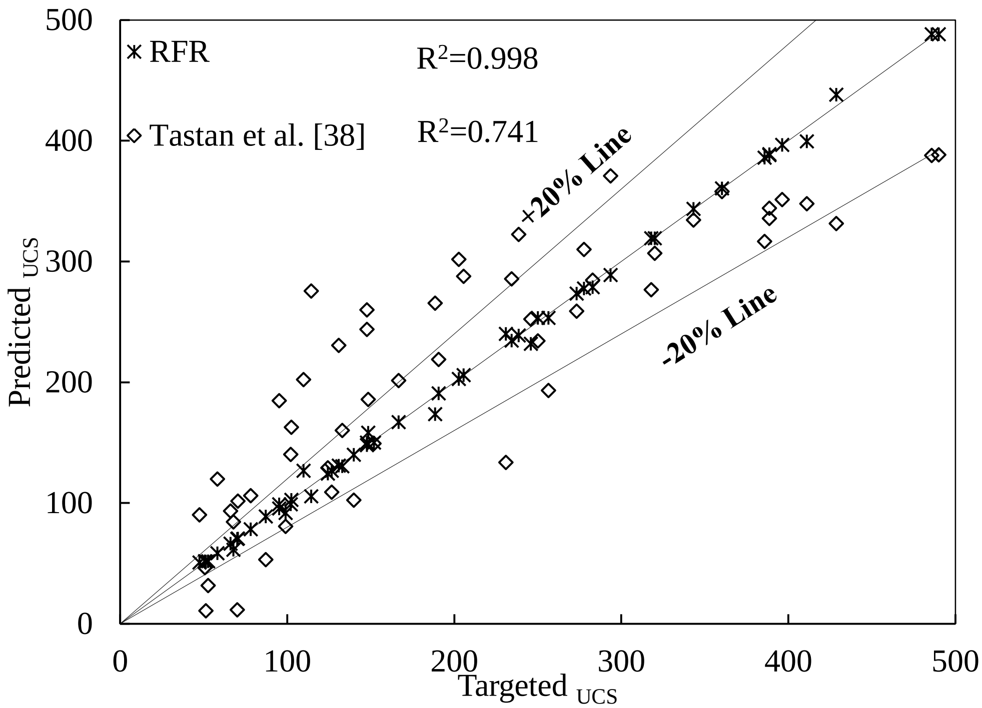

Fig. 2. Comparison of targeted versus predicted unconfined compressive strength using R.F.R. with literature.

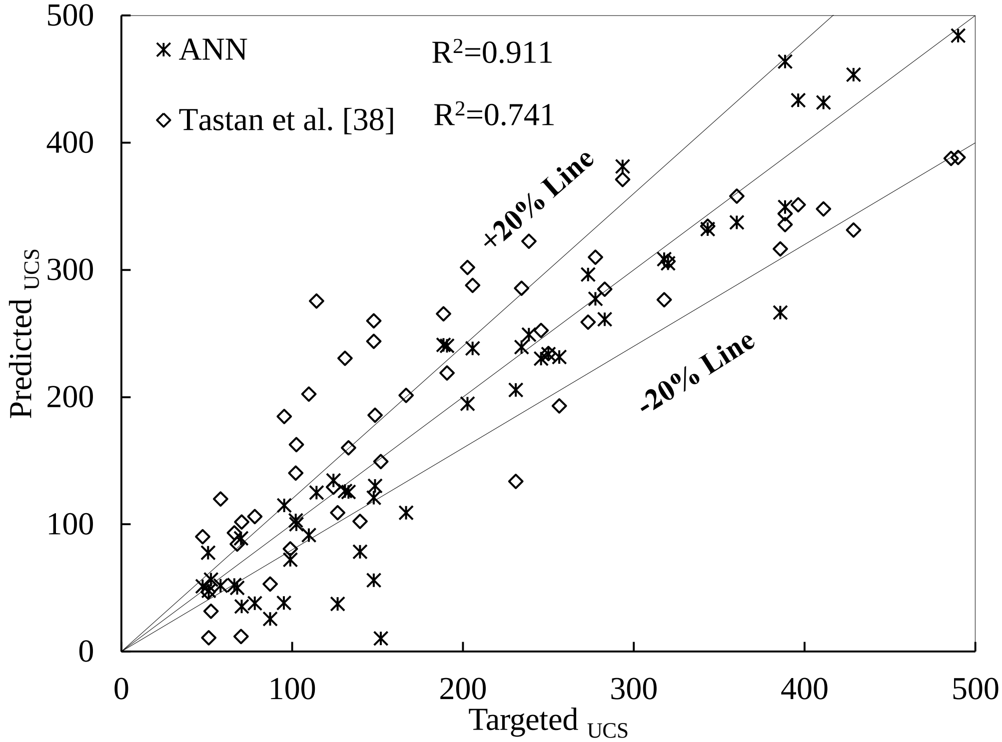

Fig. 3. Comparison of targeted versus predicted unconfined compressive strength using A.N.N. with literature.

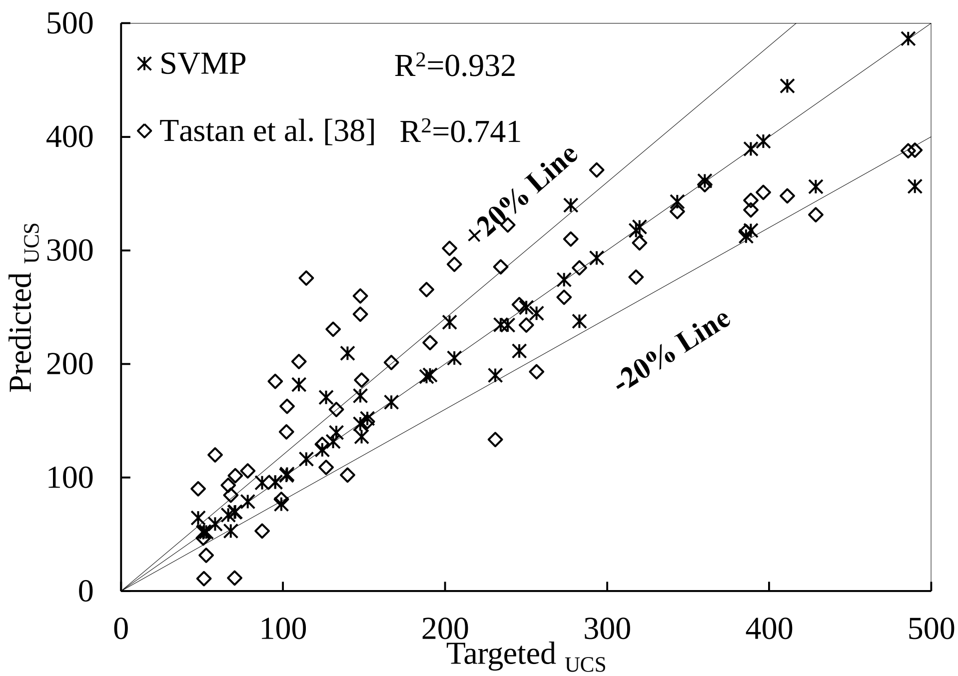

Fig. 4. Comparison of targeted versus predicted unconfined compressive strength using S.V.M.P. with literature.

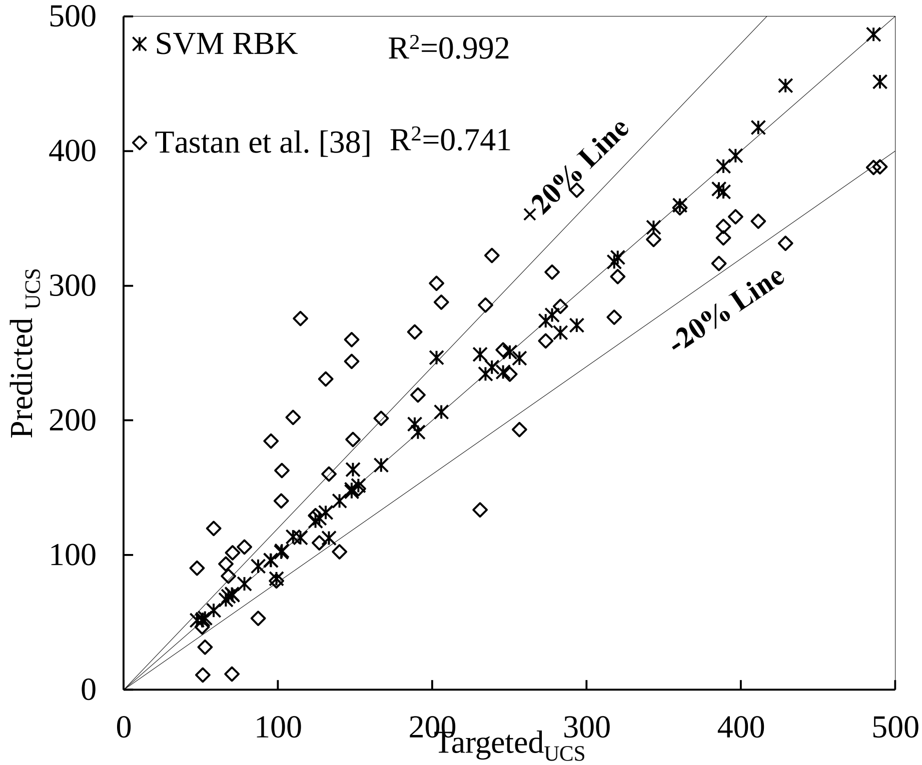

Fig. 5. Comparison of targeted versus predicted unconfined compressive strength using S.V.M.R.B.K. with literature.

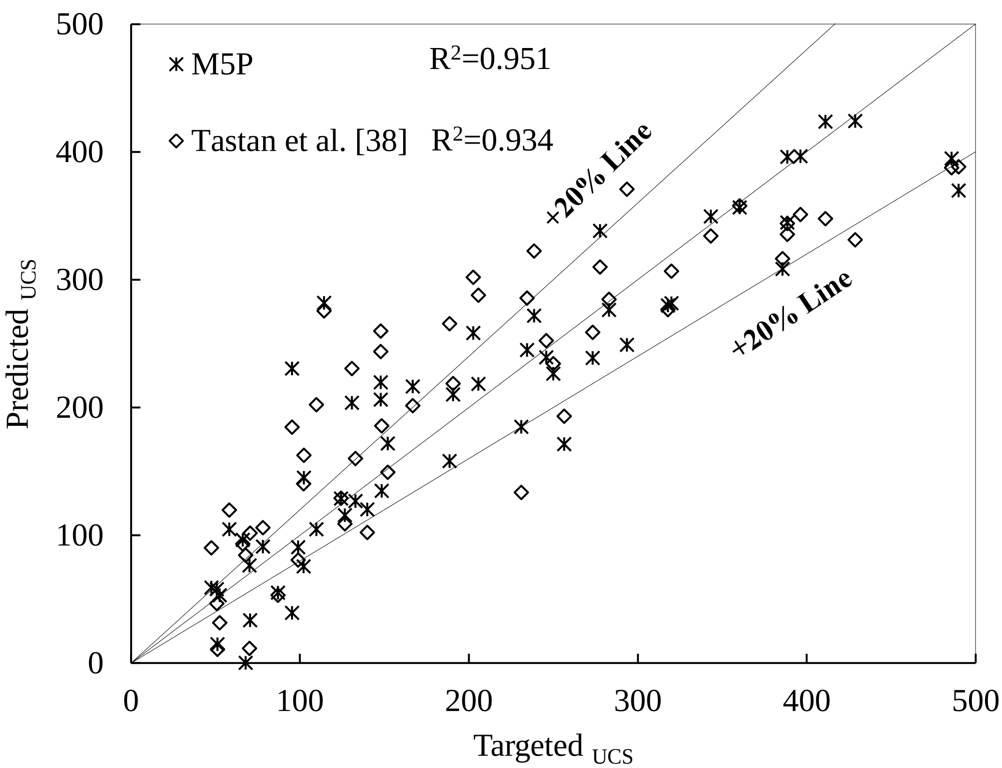

Fig. 6. Comparison of targeted versus predicted unconfined compressive strength M5P with literature.

Fig. 2 to Fig. 6 provide a comparison of the R.F.R., A.N.N., S.V.M.R.B.K., S.V.M.P., and M5P with one described in the literature. When compared to Tastan et al [30]'s equation, most of the estimated parameters using R.F.R., A.N.N., S.V.M.R.B.K., S.V.M.P., and M5P models were frequently well within limit of 20% lines, leading in higher values of r and R^2. In compared to [30], the created models already showed reduced values of inaccuracy indices in Fig. 1. The maximum deviation with respect to experimental values predicted by R.F.R., A.N.N., S.V.M. R.B.K., S.V.M.P., and M5P models can be estimated as 15.38, 93.29, 20.59, 65.48 and 146.08 whereas the maximum deviation with the use of equation 1 reported by [30] is obtained as 224.23. It implies that all the developed models behave superiorly in comparison to that reported in literature [30]. Further the R.F.R., S.V.M.R.B.K. can be used for reliable prediction of UCS for fly ash stabilized organic clay as the error involved with the use of these models is lesser in comparison to other models. Finally, out of the five models, best model (SVMRBK) was selected to distinguish the comparison of predicted and targeted for different soils (Markey peat, Lawson soil and Theresa soil) as shown in the Fig. 7.

Hence, the proposed model is having the capability to predict the UCS for the fly ash stabilized organic clay within a range of ±20.

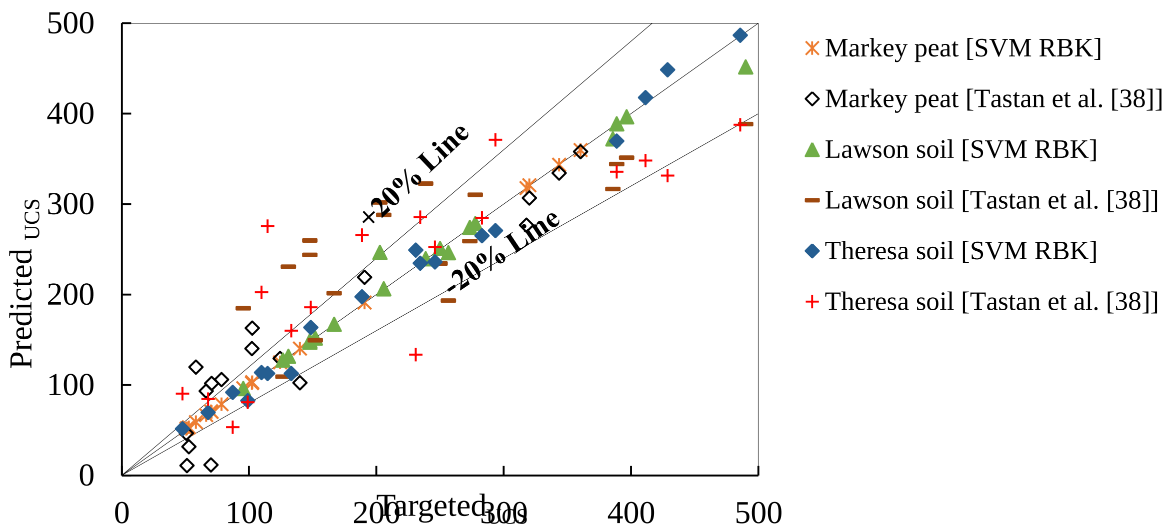

Fig. 7. Comparison of prediction from SVM RBK model with the targeted one for different soils.

6. Sensitivity analysis

To investigate the impact of various model parameters on the outcome (unconfined compressive strength), a sensitivity analysis was conducted for the best fit models, namely the R.F.R. and S.V.M.R.B.K. models. The varied combinations of input parameters were employed for this goal. One of the input parameters was deleted from each combination, and thus the influence of such an omitted variable upon that outcome being assessed using performance indicators (r, R^2, M.S.E., R.M.S.E., M.A.E. & M.A.P.E.). Tables 3 and 4 demonstrate the computed values of these performance metrics in different scenarios. An examination of the error parameters shown in Tables 3 and 4 revealed that the Cao to Sio2 ratio, followed by fly ash (FAper), had the greatest effect on the estimation of the unconfined compressive strength of such organic soil stabilized with fly ash. This observation was on lines similar to that reported by [30]. A further study of Table 3 suggests that the pH of soil is not likely to have any significant influence on the output. The outcome of sensitivity analysis also suggests that the present combination of input variables likely to provide the unconfined compressive strength of the organic soil with least possible error.

Table 3
Sensitivity analysis for the R.F.R.

Pairings of input variables	Input variable omitted	R.F.R.					
		r	R^2	*M.S.E.*	*R.M.S.E.*	*M.A.E.*	*M.A.P.E.*
Cao/Sio_2, OC, FA_{per}, UCS_0, pH	--	0.996	0.9742	321.07	17.92	14.35	8.69
OC, FA_{per}, UCS_0, pH	Cao/Sio_2	0.931	0.9043	836.92	28.93	23.42	14.41
Cao/Sio_2, FA_{per}, UCS_0, pH	OC	0.974	0.9400	535.10	23.13	17.60	10.76
Cao/Sio_2, OC, UCS_0, pH	FAper	0.952	0.9261	739.34	27.19	19.77	12.05
Cao/Sio_2, OC, FA_{per}, pH	UCS_0	0.995	0.9610	482.34	21.96	16.58	10.03
Cao/Sio_2, OC, FA_{per}, UCS_0	pH	0.985	0.9720	432.72	20.80	16.20	9.93

Table 4
Sensitivity analysis for the S.V.M.R.B.K.

Pairings of input variables	Input variable omitted	S.V.M.R.B.K.					
		r	R^2	*M.S.E.*	*R.M.S.E.*	*M.A.E.*	*M.A.P.E.*
Cao/Sio_2, OC, FA_{per}, UCS_0, pH	--	0.999	0.9605	1174.09	34.26	31.46	17.38
OC, FA_{per}, UCS_0, pH	Cao/Sio_2	0.917	0.5746	12504.55	111.82	101.74	71.75
Cao/Sio_2, FA_{per}, UCS_0, pH	OC	0.961	0.8682	6238.12	78.98	59.68	35.25
Cao/Sio_2, OC, UCS_0, pH	FAper	0.926	0.6445	11247.18	106.05	91.97	65.60
Cao/Sio_2, OC, FA_{per}, pH	UCS_0	0.984	0.8625	5098.16	71.40	61.12	40.43
Cao/Sio_2, OC, FA_{per}, UCS_0	pH	0.993	0.9467	2782.69	52.75	41.50	27.82

7. Conclusions

The use of soft computing algorithms to the prediction of unconfined compressive strength of fly ash stabilized organic clay was investigated in this research. The following conclusions are drawn from the results and discussion.

1. In predicting the unconfined compressive strength of stabilized organic clay, all developed models outperformed the equation reported in the literature.
2. Among the developed models, R.F.R. had the most accurate predictions, followed by S.V.M.R.B.K., S.V.M.P., A.N.N., and M5P.
3. The ratio of Cao to Sio2 has the greatest impact on the unconfined compressive strength of fly ash-stabilized organic clay, while the pH of the soil has the least impact.

The outcome of study suggests that the R.F.R. model can be used for the reliable prediction of unconfined compression strength of fly ash stabilized organic clay and further it may remove the need of performing the time and cost prohibitive experiments on the same.

Notations

R.F.R.	Random forest regression
A.N.N.	Artificial neural networks
S.V.M.R.B.K.	Support vector machine radial basis kernel
S.V.M.P.	Support vector machine poly kernel
M5P	M5P model tree
Cao	Calcium oxide
Sio2	Silicon dioxide
OC	Organic content
FA_{per}	Fly ash percentage
UCS_0	Unconfined compressive strength of organic clay without fly ash
pH_{mix}	pH of soil-fly ash
UCS	Unconfined compressive strength of organic clay stabilized with fly ash
R^2	Coefficient of determination
GPU	Graphics processing unit
r	Correlation coefficient
M.S.E.	Mean square error
R.M.S.E.	Root mean square error
M.A.E.	Mean absolute error
M.A.P.E.	Mean absolute percentage error
k, m, I, d, C, γ, M	User defined parameters

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

TG: Conceptualization; TG, RKD, VNK: Data curation; TG: Formal analysis; TG: Investigation; TG, RKD, VNK: Methodology; TG: Project administration; TG: Resources; TG: Software; RKD, VNK: Supervision; TG: Validation; TG: Visualization; TG: Roles/Writing – original draft; TG, RKD, VNK and MSK: Writing – review & editing.

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