Research Article

The effect of data size of ANFIS and MLR models on prediction of unconfined compression strength of clayey soils

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Abstract
The shear strength (S_u) of soils is one of the most widely used parameters for designing structures safely, where Su is found with the unconfined compression test (UCS). Although UCS can be acquired by performing uniaxial compression test it would be extremely helpful to predict the UCS without performing any compression test, namely, using computational methods considering different parameters of soils such as consistency limits, fine grain ratio, liquidity index, and void ratio. The goal of present work is predicting UCS taking into account these soil parameters with the aid of developed Adaptive Neuro-Fuzzy Inference System (ANFIS) model and the Multiple Linear Regression (MLR) analyses. On the other hand, the effect of the size of the training set of designed models on the results is examined, also. For this aim, four different models composed of different training and test set ratios have been constructed and analyzed using ANFIS and MLR. It is concluded that UCS can be predicted using MLR analysis and ANFIS model with best 0.76 and 0.91 values of determination coefficient (R^2) around the x = y line respectively, and the effect of the size of the training set of models on ANFIS is more pronounced than MLR models.

Keywords Multiple linear regression · Adaptive neuro fuzzy inference system · Unconfined compression strength

1 Introduction

The stress–strain behavior and shear strength of soils need to be addressed exactly for the safe design of structures. Therefore, compression and shearing tests are performed on the specimens taken from field for describing the stress–strain behavior and shear strength of soils. In this context, the uniaxial compression test is used for cohesive soils while undrained shear strength (Su) is preferred for geotechnical design [1].

The UCS is the basic strength parameter of clayey soils and it refers to the maximum axial pressure that beared by sample until it fails or it's axial strain arrives at 20% on the area of cross sectional at the failure [2]. The determination of UCS in laboratory is exhausting, time consuming, highly priced and it is difficult to take undisturbed sample for tests [3]. Hence, the prediction of UCS in a direct way is an important concern for engineers and scientists for long years [4].Recently, single variable regression is employed for the relationships between UCS and dimensions of specimens [5, 6], UCS and height to diameter ratio [7, 8], undrained shear strength and water content [9–11] while multiple variable regression is performed for the relationship between undrained shear strength and water content [2, 3, 12, 13]. Furthermore, adaptive neuro-fuzzy interference systems (ANFIS) and artificial neural networks (ANNs) are utilized for UCS of soils [14–16].

From the inspection of open literature, it is found that although there are numerous studies on examination of prediction capibility of UCS using MLR analysis and ANFIS models; the number of studies considering the effect of the size of the training set of models is limited. The goal of present work is predicting UCS taking into account soil parameters such as specimen diameter (D), specific

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Table 1 Geotechnical properties of soils

Soil name	Specific gravity (Gs)	Fine content (%)	Liquid limit (%)	Plasticity index (%)	Optimum moisture content (%)	Maximum dry density (kN/m^3)	Soil type
Istanbul clay 1	2.62	85	96.2	62.2	33	11.9	CH
Mugla clay	2.72	93	104.3	74.3	34	12.1	CH
Istanbul clay 2	2.76	100	56.6	35.6	21	16.3	CH
Burdur clay	2.73	100	46.7	27.2	24	15.3	CL
Istabul clay 3	2.84	100	84	60	32	13.8	CH
Test standard	[17]	[18]	[19]	[19]	[20]	[20]	(USCS)

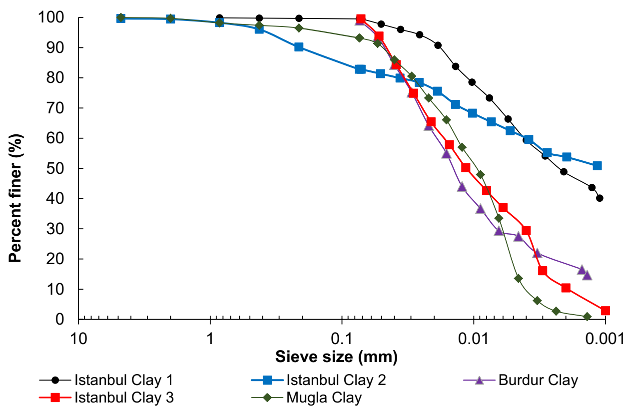

Fig. 1 Particle size distribution curves for soils

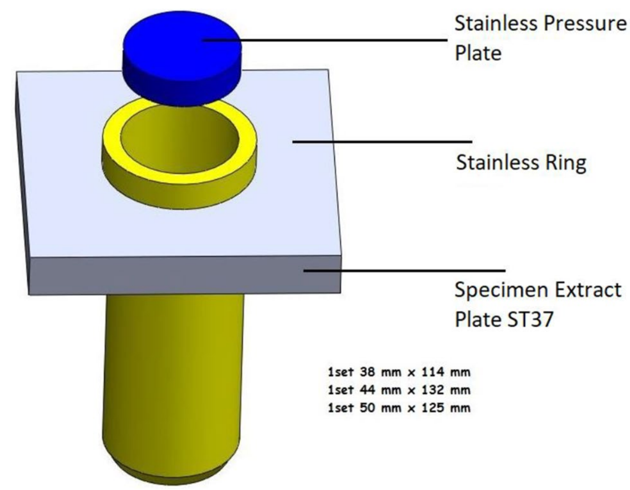

Fig. 2 The scheme of samplers

gravity (Gs), plasticity index (PI), liquidity index (LI), void ratio (e), content of sand (S) and content of clay (C) using multiple linear regression (MLR) and adaptive neuro-fuzzy interference systems (ANFIS), and examining their talents by means of some statistical criteria, i.e. determination coefficient (R^2), root mean square error (RMSE) and mean absolute percentage error (MAPE).

2 Data and material

The samples used in this study are low and high plasticity clays that have been taken from different cities of Turkey, i.e. Istanbul, Burdur and Mugla. The geotechnical tests have been carried out considering American Society of Testing and Materials (ASTM). The geotechnical properties of soils are tabulated in Table 1 and particle size distributions illustrated in Fig. 1.

Soil samples are collected from different five fields and oven-dried after they are transported to laboratory. After, they have sieved through 2.38 mm in order to see the effect of sand in some soils, and then they subjected to tests specific gravity, particle size distribution, consistency limits and standard compaction tests as per [17–20] respectively. Finally, soils are classified regarding these test result in the view of Unified Soil Classification System (USCS).

3 Methodology

3.1 Preparing Specimens

At first, soils had sieved and then oven-dried before it compacted. Compaction is carried out following standard proctor compaction test in proctor mold in three layers and each layer is subjected to the energy of 25 fall of standard compaction hammer from the height of 30 cm. In addition, the water content of soils has various values while they are compacted, and it is aimed to provide at least three different water contents as optimum, wetter and drier of optimum for each soil.

Schematic illustration of these samplers with 38 mm, 44 mm and 50 mm diameter is presented in Fig. 2. Specimens are obtained by driving the sampler into the mold and extracting specimen from the sampler with hydraulic jack (Figs. 3, 4). Then specimens have been stored 24 h in stretch nylon in order to make the water scattered as

Fig. 3 Driving the sampler into the mold by hydraulic jack

Fig. 4 Extracting down the specimen from the sampler with hydraulic jack

homogeneous without losing any water as applied by [21]. After 24 h specimens have been subjected to the uniaxial compression test for determining UCS.

In this study, totally sixty-eight specimens of three different soils in three different diameters and various water contents are tested.

3.2 Data and methods

3.2.1 Data

The data are obtained by conducting wide range of geotechnical tests which have the particle size distribution, consistency limits, standard proctor compaction, specific gravity and uniaxial compression tests. Particle size distribution tests include sieve analysis test and hydrometer analysis test by [18]. The consistency limits contains liquid limit, plasticity limit and plasticity index. The liquid limit is determined by using Cassagrande equipment in accordance with [19] and the plastic limit is defined 3 mm rod formation method. The compaction parameters such as maximum dry density and optimum moisture content are determined conducting Standard Proctor compaction test in the view of [20]. The uniaxial compression tests are performed by [22] for identifying the unconfined compression strength of soils and the schematic representation of testing machine of this test is presented in Fig. 5 [3].

Cylindrical soil specimens prepared with 38 mm, 44 mm and 50 mm diameters and 76 mm, 88 mm and 100 mm heights respectively are subjected to the increasing axial compression load until the samples fail. Later, the UCS is calculated by means of Eq. 2 given below:

$$\mathrm{UCS} = \frac{P}{A} \tag{2}$$

where P is the maximum axial load before failure and A is the cross-section area of the specimen at the time of failure.

In this study, four different models are created with sixty-eight total data and every data consists of seven independent and one dependent variables. Independent variables are specimen diameter (D), specific gravity (Gs), plasticity index (PI), content of sand (Sand %), content of clay (Clay %), void ratio (e), liquidity index (LI) and the dependent variable is unconfined compression strength (UCS). The descriptive statistics of data is presented in Table 2.

Four different models with different training size are constructed for determining the effect of the size of training set on prediction capability of ANFIS and MLR analyses. Model

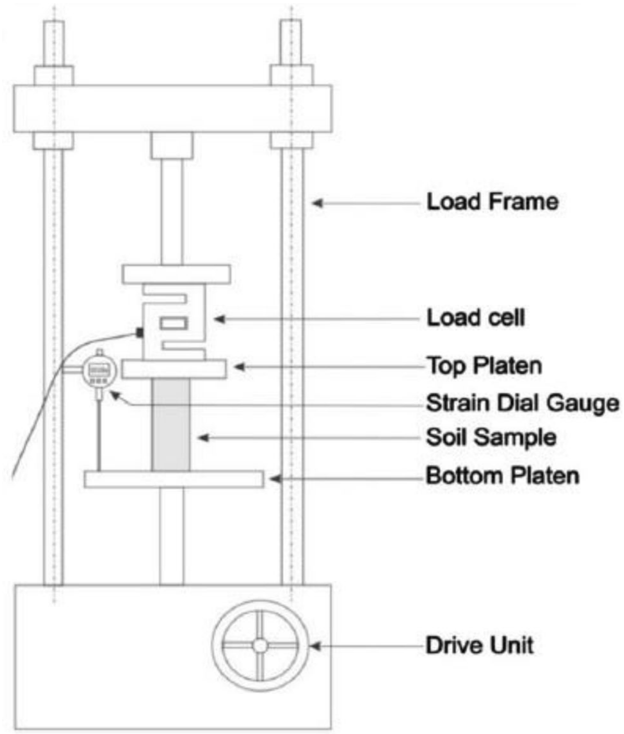

Fig. 5 Schematic drawing of an unconfined compression test machine [3]

1, Model 2, Model 3 and Model 4 have 80%, 70%, 60% and 50% of all data as training set respectively and rest of data is used as test set for each model.

3.3 Multiple linear regression (MLR)

MLR is a statistical method for determining the relationship between two or more variables by fitting a linear equation to a known output value [23, 24]. MLR uses different linear combinations of variables as regression equation [25] and best equation is selected based upon the highest correlation coefficient and lowest F-ratio [26] in a way to minimize sum of square residuals [27]. The universal equation for MLR is given below [15]:

$$y = a_0 + a_1x_1 + a_2x_2 + a_3x_3 + L + a_nx_n + \varepsilon \tag{3}$$

where y is the dependent variable; x_i is the independent variable; a_0 is a constant; a_i is a scope associated with x_i and ε is an error [28].

In the present study, MLR analyses are performed with stepwise and enter methods, and prediction models are established with the SPSS 17 Software. Enter method puts every independent variable into the analyses but stepwise method picks variables, which are statistically effective on prediction, and which increase adjusted R^2 of regression equation applying different variable combinations.

3.4 Adaptive neuro-fuzzy interference systems

The most important property of fuzzy models makes them more attractive compared to other traditional methods is the capability of defining complicated and multivariable nonlinear issues [29].

Fuzzy set consists of objects with a continuum membership grades. In this set every object has been given a grade of membership changing zero to one by the function of membership [30]. Jang [31] has proposed ANFIS that compounds the neural network and the fuzzy logic. Therefore, ANFIS can achieve in solving complex and nonlinear problems without any uncertainty [32]. It is able to obtain higher estimation ability compared to a single methodology alone since there is learning capability of a neural network and reasoning capability of fuzzy logic together in ANFIS [33].

The target of ANFIS is to set a model that will accurately associate the input values with the output values and the simple FIS is presented in Fig. 6.

ANFIS architecture comprises of five layers that each have neurons and number of neurons changes depending on the number of rules. The characteristic structure of an ANFIS model that has two input variables is presented in Fig. 7. We can suppose a fuzzy inference system has two inputs represented by x and y, and one output to make definition easier. A usual if- then rule cluster with two fuzzy for a first-order Sugeno fuzzy model is described as below [32]:

$$\text{Rule 1}: \text{ If x is } B_1 \text{ and y is } A_1, \text{ then } f_1 = c_1x + d_1y + e_1 \tag{4}$$

Table 2 Descriptive statistics of data set for prediction of UCS

	Specific gravity (Gs)	Diameter of specimen D (mm)	Liquidity index	Void ratio (e)	Clay (%)	Sand (%)	Unconfined compression strength (UCS) (kPa)
Mean	2.73	43.57	0.07	0.98	26.74	4.91	198.55
Minimum	2.62	38	−0.14	0.61	5	0	24.61
Maximum	2.84	50	0.28	1.34	55	15	492.37
Std. deviation	0.73	5.04	0.09	0.22	21.08	6.04	97.07

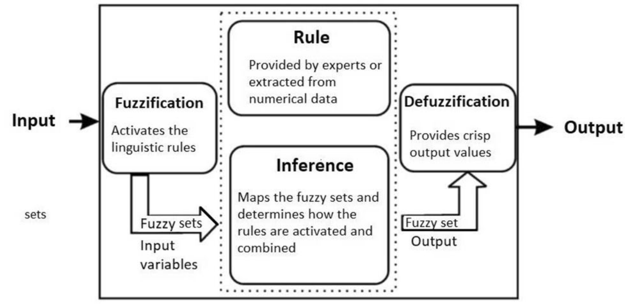

Fig. 6 The simple fuzzy inference system [16]

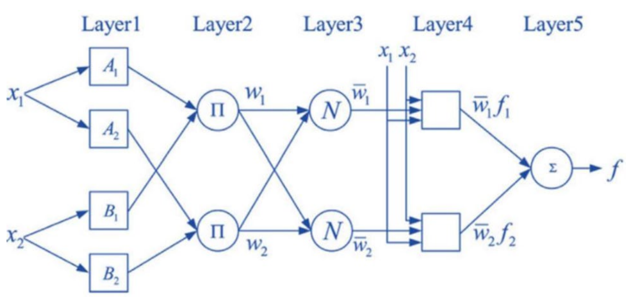

Fig. 7 A characteristic ANFIS structure of a two input model [34]

$$\text{Rule 2}: \text{ If x is } B_2 \text{ and y is } A_2, \text{ then } f_2 = c_2x + d_2y + e_2 \tag{5}$$

where $\{c_i, d_i, e_i\}$ is the set of parameters belongs to this node.

Layer 1 is called the fuzzification layer and creates the membership functions (MFs) for inputs by Eqs. 6–7 [35].

$$O_{1i} = \mu A_i(x) \quad i = 1, 2 \tag{6}$$

$$O_{1i} = \mu B_{i-2}(x) \quad i = 3, 4 \tag{7}$$

Here μA_i and μB_i are the membership degrees for A_i and B_i that are parameters of fuzzy set and calculated by Eq. 8.

$$\mu A_i = e^{-\frac{1}{2}\left(\frac{x-c}{a}\right)^2} \quad i = 1, 2 \tag{8}$$

where a_i defines the variances of the MF and c_i characterizes the centre of MF.

Layer 2 is called rule layer, each nodes denotes by the fuzzy interference system (FIS) and this layer signifies the firing strength of rules (Eq. 9). Cell count is equal to the count of rule in this layer [36].

$$O_{2i} = w_i = \mu A_i(x) \cdot \mu B_i(y) \quad i = 1, 2 \tag{9}$$

Layer 3 is normalization layer and calculates the normalized firing strength what represents the ratios of firing strength ith rule to sum of all firing strengths (Eq. 10).

$$O_{3i} = \overline{w_i} = \frac{w_i}{w_1 + w_2} \quad i = 1, 2 \tag{10}$$

Layer 4 is defuzzification layer, the output of nodes is called conclusion parameters basically the product of first order polynomial and normalised firing strength by Eq. 11 [37].

$$O_{4i} = \overline{w_i} \cdot f_i = \overline{w_i} \cdot (p_i x + p_i y + r_i) \quad i = 1, 2 \tag{11}$$

Layer 5 is called the sum layer and in this layer there is just one node. This layer totals the whole output summation of arriving signals by Eq. 12 [38].

$$O_{4i} = f = \sum \overline{w_i} \cdot f = \frac{\sum wi \cdot f_i}{\sum wi \cdot} \quad i = 1, 2 \tag{12}$$

Figure 8 shows the schematic representative structure of the ANFIS model with three inputs and one input [39]. In scope of this study, seven input variables (D, Gs, PI, Sand %, Clay %, e, LI) and one output variable (UCS) are used for all models. Thus, the input layer with seven neurons and output layer with one neuron in the ANFIS model is used in this study.

To enhance the capacity of generalization of ANN input and output variables are normalized in the range of [0,1] by the formula employed in Eq. 13 [16].

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{13}$$

where X is the data to be normalized, X_{norm} is the normalized value of X, X_{min} and X_{max} are the minimum and maximum value of data.

In this study, a hybrid learning algorithm is employed as an optimization method during the learning stage of the ANFIS model. In addition, the back-propagation gradient descent method and the least-squares method employed together to emulate FIS membership functions of training data set. Then, the generalized gauss-shape fuzzy membership function with three numbers of membership functions is performed for the ANFIS analysis. ANFIS is executed with Matlab R2015a software. In ANFIS models, the data used in

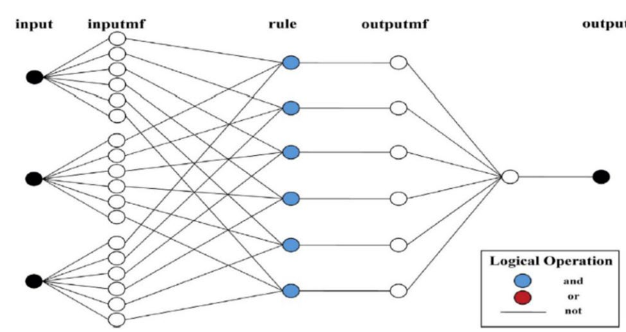

Fig. 8 The schematic representative structure of the ANFIS model [39]

real values and normalized values so that it has been tried to see the difference between results and make a conclusion. Table 3 shows detailed parameter of training the FIS.

3.5 Evaluation criteria

Talents of the ANFIS and MLR models for predicting UCS are evaluated and compared by means of root mean square error (RMSE), mean absolute percentage error (MAPE), determination coefficient of scattering around the best fit line determined by least squares method (R^2) and determination coefficient of scattering around the x=y line what represents the 100% accuracy of predictions, that intersects the origin and its inclination is 45° (R^2 (45°)). The following formulas are used to determine these evaluation criteria:

$$\mathrm{RMSE} = \sum_{i=1}^{n} \sqrt{\frac{(x_i - y_i)^2}{n}} \tag{14}$$

$$\mathrm{MAPE} = \sum_{i=1}^{n} \frac{\left| \frac{x_i - y_i}{x_i} \right|}{n} \tag{15}$$

Table 3 Detailed parameters of training FIS

Parameter	Description/value
Fuzzy structure	Sugeno
Membership function type	Gaussmf
Output membership function	Constant
Number of membership functions associated with each input	3
Number of inputs	7
Number of outputs	1
Optimization method	Hybrid (last square and back-propagation)
Training maximum epoch number	100

$$R^2 = \frac{n \cdot \sum_{i=1}^{n} x_i y_i - \sum_{i=1}^{n} x_i * \sum_{i=1}^{n} y_i}{\sqrt{\left[n \cdot \sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2\right] * \left[n \cdot \sum_{i=1}^{n} y_i^2 - \left(\sum_{i=1}^{n} y_i\right)^2\right]}} \tag{16}$$

$$R^2(45^\circ) = \frac{\sum (y_i - \overline{y_i})^2 - \sum (y_i - x_i)^2}{\sum (y_i - \overline{y_i})^2} \tag{17}$$

where x is observed and y is predicted value of UCS and n is the number of values in data sets.

4 Results

4.1 MLR analysis

The R^2, R^2 (45°), RMSE and MAPE of models developed by MLR stepwise method and MLR enter method is presented in Table 4.

The accuracy of predictions is evaluated based upon the R^2 (45°) because R^2 is calculated around best fit line and it represents good relationship between predictions and observations but not 100% accuracy. As seen in Table 4 enter method MLR analysis is more successful than stepwise method MLR analysis in predicting UCS according to the R^2 (45°) values even though the difference is not much at all. This shows that in stepwise method MLR analyses even if some parameters are excluded from the analysis because of they are considered statistically insignificant, but they contribute to obtain more accurate estimates. It may be said Gs, PI and Sand % play a vital role to predict the UCS although they don't seem effective statistically (Table 5).

In addition, Model 1 seems as the most successful model when compared to the others (Table 4). Model 1 has the largest training set and it can be said that larger training set generally contributes to obtain more accurate

Table 4 Statistic evaluation of models analyzed by MLR

	Share of training data (%)	Analysis method	R^2	R^2 (45°)	RMSE (kPa)	MAPE (%)
Model 1	80	Enter	0.88	0.76	31.44	14
		Stepwise	0.87	0.73	33.46	16
Model 2	70	Enter	0.83	0.52	43.26	16
		Stepwise	0.74	0.41	49.38	18.2
Model 3	60	Enter	0.83	0.65	36.13	15.8
		Stepwise	0.83	0.62	38.11	18.1
Model 4	50	Enter	0.86	0.69	34.59	16
		Stepwise	0.85	0.62	37.55	19.3
Means		Enter	0.85	0.66	36.34	15.45
		Stepwise	0.83	0.60	39.63	17.90

Table 5 The coefficients for predicting UCS from MLR analyses of model 1

	Constant	Specimen diameter D (mm)	Specific gravity Gs	Plasticity index PI (%)	Sand (%)	Clay (%)	Void ratio e	Liquidity index LI
Enter method analysis	0.686	−0.155	1.258	−0.614	1.690	−0.502	−0.172	−1.212
Stepwise method analysis	1.111	−0.135	–	–	–	−0.143	0.438	−1.259

results but it is not consistent every time. Thus, determining the optimum training and test sets are the most important part of the exact predictions.

The coefficients of MLR analyses are presented in Table 5 and the equation obtained from Enter Method MLR analysis is given in Eq. 18.

$$UCS = 0.686 - 0.155\,D + 1.258\,Gs - 0.614\,PI + 1.690\,Sand\,(\%) - 0.502\,Clay\,(\%) - 0.172\,e - 1.212\,LI \tag{18}$$

where D is specimen diameter; Gs is specific gravity; PI is plasticity index; Sand (%) is percent of sand; Clay(%) is percent of clay; e is void ratio and LI is liquidity index.

4.2 ANFIS models

The cross plot for observed and predicted UCS values are illustrated in Fig. 9 and R^2, R^2 (45°), MAPE and RMSE values are tabulated in Table 6. Model 2 is the most successful model to predict UCS of soils according to R^2, R^2 (45°), MAPE and RMSE. As seen in Table 6 and Fig. 9, R^2 (45°) value is 0.91 for Model 2 where it is 0.63 for Model 4 and it can be said it is success in prediction decreases around 30% by decrease in the size of training data set from 80% to 50%.

It is found that the ANFIS models with normalized data can predict UCS more accurately compared to the models with real data. This finding can be apparently seen especially in Model 3 and Model 4 though not in Model 1 and Model 2. It is concluded that the use of normalized or real data have significant effect on the achievement of prediction.

ANFIS outputs reveal that UCS increases with the increase of percent of clay and increases till a certain values of void ratio but then decreases (Fig. 10), UCS generally decreases with the increase of diameter but except in very small void ratio values (Fig. 11), it does not have a certain behavior when it is examined in terms of diameter and

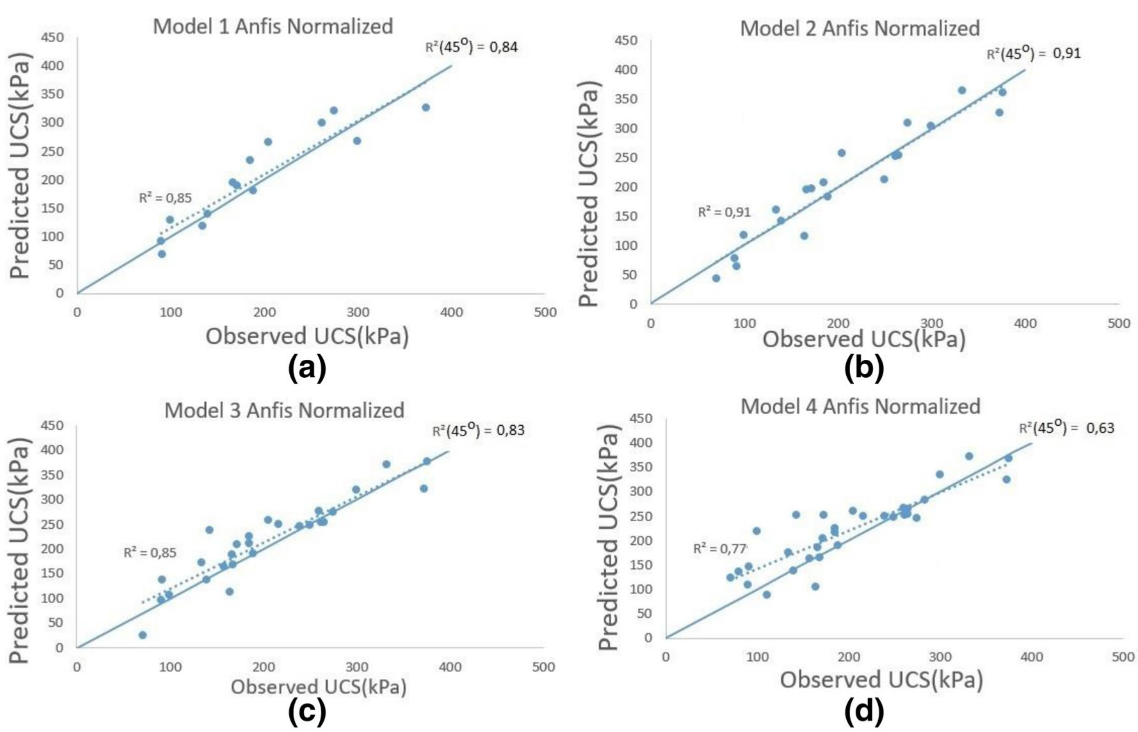

Fig. 9 The cross plot for observed and predicted UCS values obtained by ANFIS model with normalized data

Table 6 Statistical evaluations of models made by ANFIS

	Share of training data (%)	Input values	R^2	R^2 (45°)	RMSE (kPa)	MAPE (%)
Model 1	80	Real data	0.84	0.82	34.35	17
		Normalized data	0.85	0.84	33.26	17
Model 2	70	Real data	0.91	0.91	27.82	14.2
		Normalized data	0.91	0.91	26.67	17
Model 3	60	Real data	0.74	0.68	60.28	27.2
		Normalized data	0.86	0.83	33.44	18.9
Model 4	50	Real data	0.62	0.60	55.21	21
		Normalized data	0.77	0.63	43.88	28.4
Mean		Real data	0.77	0.75	44.45	19.85
		Normalized data	0.85	0.80	26.81	20.33

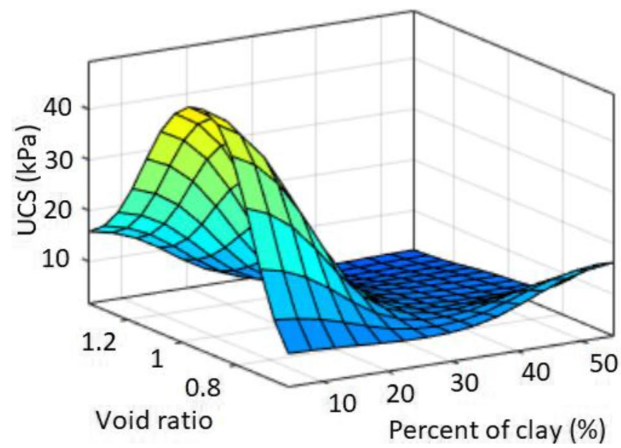

Fig. 10 ANFIS output for unconfined compression strength as a function of void ratio and percent of clay

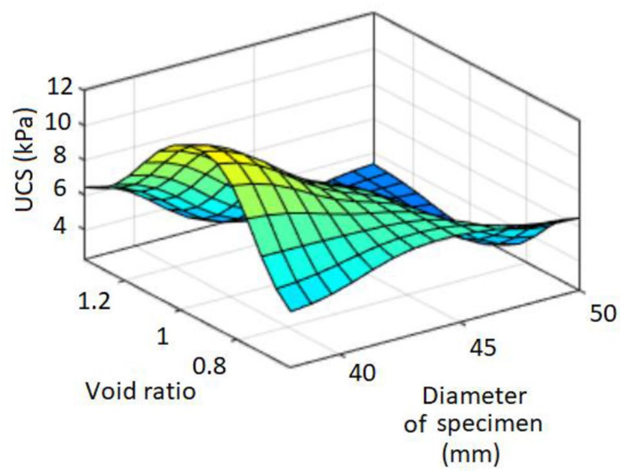

Fig. 11 ANFIS output for unconfined compression strength as a function of void ratio and diameter of specimen

percent of clay (Fig. 12) and UCS generally increases with the increase in plasticity index (Fig. 13).

4.3 Comparison of MLR analysis and ANFIS models

The correlations between observed and predicted values of UCS by ANFIS and MLR analyses belong to Model 1 shown in Fig. 14.

R^2 (45°) values of ANFIS model with real data and normalized data are 0.82 and 0.84 respectively and R^2 (45°) values of MLR analyses that are carried out using enter method and stepwise method are 0.76 and 0.73 respectively (Fig. 8). So ANFIS models are more successful than MLR models even if it is not much at all, MLR analyses are more successful when they are executed by using enter method compared to stepwise method and ANFIS models give more accurate predictions while models developed with normalized data than while models developed with real data. Furthermore, residual errors of UCS predictions of Model 1 and Model 4 structured by MLR and ANFIS are

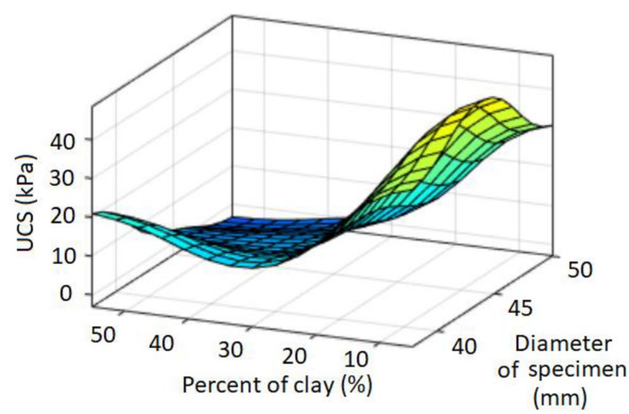

Fig. 12 ANFIS output for unconfined compression strength as a function of percent of clay and diameter of specimen

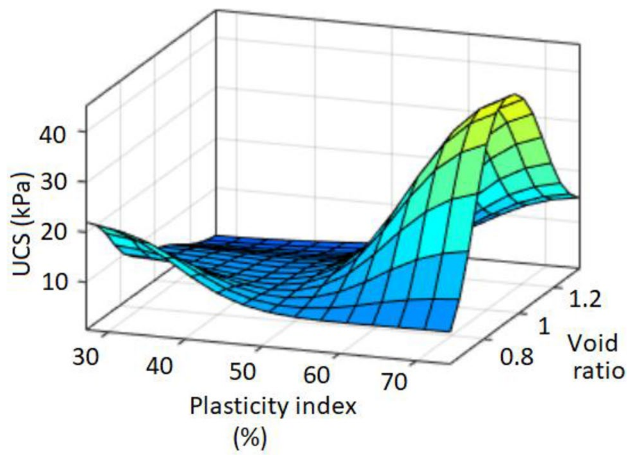

Fig. 13 ANFIS output for unconfined compression strength as a function of void ratio and plasticity index

exhibited in Figs. 15, 16 and it is seen that ANFIS analyses significantly have less error in Model 1 but it is not significant that much in Model 4 and Model 4 has extreme a few extreme devious point at such as sample of 14 and sample 25 (Figs. 15, 16).

As seen in Table 7, ANFIS models have better achievement on prediction of UCS in proportion to MLR models when mean values of R^2, R^2 (45°) and RMSE are evaluated because of bigger R^2 (45°) values and smaller RMSE values. Although R^2 values around best fit line are same it doesn't mean ANFIS and MLR models have same success in prediction because best fit line has a constant coefficient and it means there is a constant error on prediction even if all predictions are on best fit line.

5 Conclusions

The study is conducted to develop models to predict UCS of clayey soils using MLR and ANFIS and determine the effect of the size of training data on success of predictions.

The following decisions are made

(a) The predicted UCS values of ANFIS models are found to be closer to observed UCS values compared to MLR models
(b) Using normalized data for models increases the accuracy of predictions in ANFIS analyses.
(c) ANFIS model with normalized data of Model 2 exhibits almost excellent success in prediction of UCS with R^2 (45°) = 0.91 where the best model of MLR analyses is Model 1 with enter method has values of R^2 (45°) = 0.76.
(d) In ANFIS analyses, R^2 (45°) value is 0.91 for Model 2 where it is 0.63 for Model 4 and the success in predic-

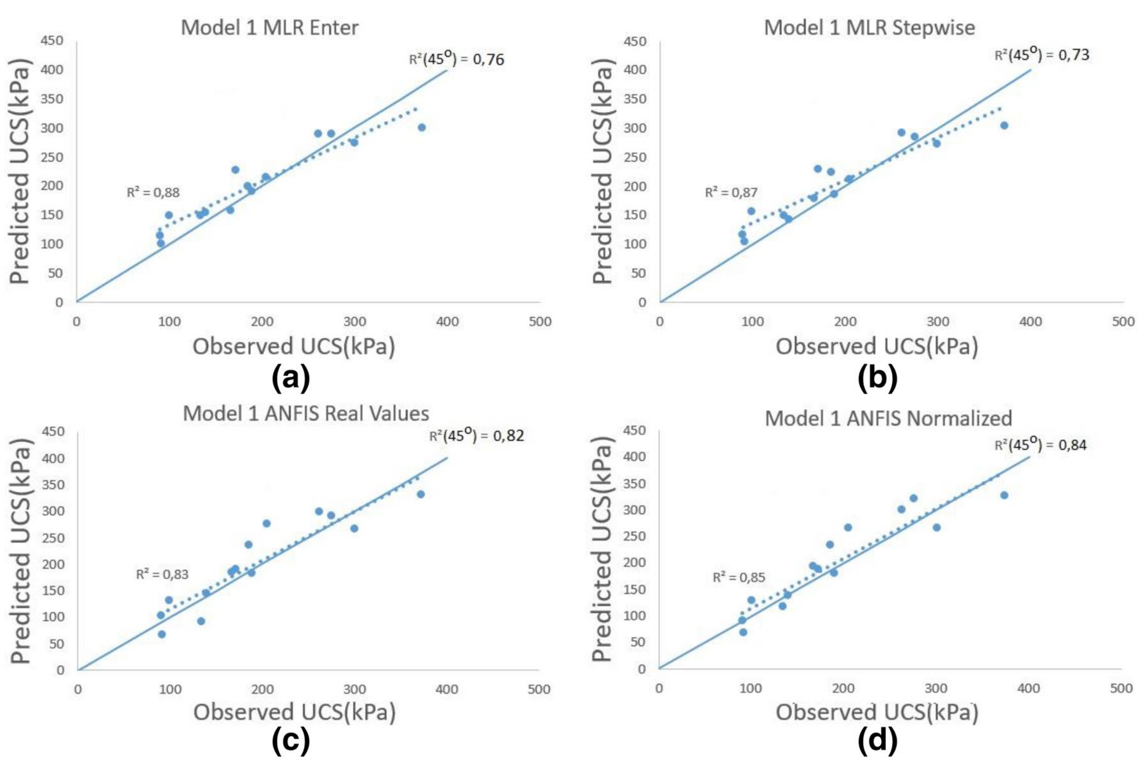

Fig. 14 The cross plot for predicted and observed UCS values of model 1

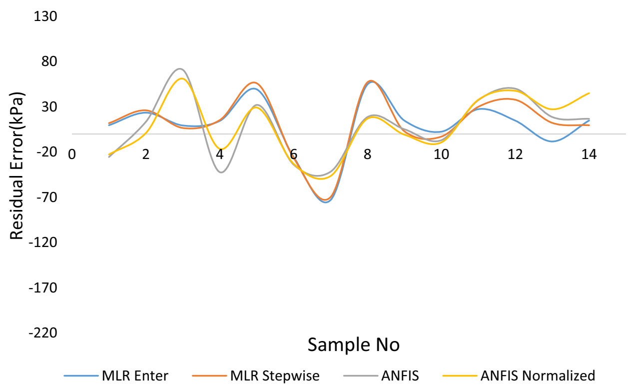

Fig. 15 Residual errors for models structured by MLR and ANFIS models for model 1

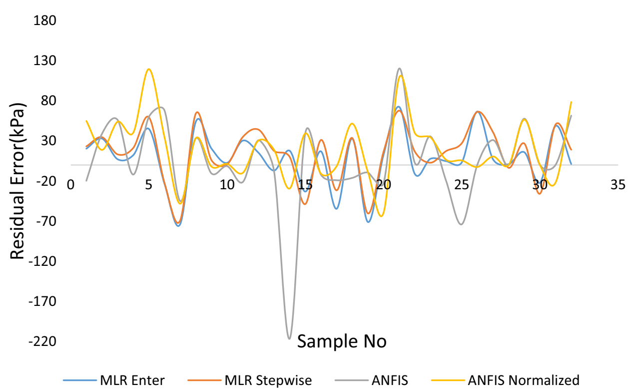

Fig. 16 Residual errors for models structured by MLR and ANFIS models for model 4

Table 7 Comparison of mean values of evaluation criteria of ANFIS and MLR models

Analysis method	R^2	R^2 (45°)	RMSE (kPa)
MLR			
Enter	0.85	0.66	36.34
ANFIS			
Normalized data	0.85	0.80	26.81

tion decreases around 30% by decrease in the size of training data set from 80 to 50%.

(e) Some parameters considered insignificant statistically are excluded from the analysis even if they contributes to obtain more accurate estimates. Thus, using enter method in MLR analysis is more successful on prediction than stepwise method.

(f) Gs, PI and Sand % play a role to predict the UCS although they don't seem meaningful statistically.

(g) ANFIS models and MLR models have enough capability to predict UCS of clayey soils with specimen and soil properties such as specimen diameter, specific gravity, plasticity index, liquidity index, void ratio, content of sand and clay.

(h) Developing training and test data set in optimum size is the most important part of obtain accurate prediction by ANFIS and MLR.

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Compliance with ethical standards

Conflict of interest There authors declare that they have no conflict of interest.

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