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Swelling Prediction in Compacted Soils Using Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

Swelling in compacted soils may lead to some damages to structures and buildings. For the sake of reducing such damages, soil swelling should be determined, so as to make the structures exhibit adequate resistance against such a phenomenon. For most cases, fully non-linear relations have been observed between soil swelling and the parameters contributing to swelling in compacted soil. As such, soil swelling should be determined via either experimentations or prediction models. However, being extremely timely, swelling tests require special expensive equipment. Accordingly, there is a need for models which can use available data to theoretically give swelling estimations of a relatively high accuracy without getting busy with swelling tests and associated issues. Investigated and evaluated in this research are the ability and application of an adaptive neuro-fuzzy interference system (ANFIS) developed by subtractive clustering and fuzzy c-mean clustering to determine and predict swelling in compacted soils. The results along with the obtained values of root mean squared error (RMSE), mean absolute error (MAE) and coefficient of correlation (R) indicated that the proposed ANFIS model succeeded to predict swelling in compacted soils at a good level of accuracy. Therefore, ANFIS models can be used to predict swelling without getting busy with swelling tests and associated issues.

KEYWORDS: Swelling of compacted soil, Subtractive clustering, Fuzzy c-mean clustering, ANFIS, Prediction.

INTRODUCTION

With the increasing trend of building construction for constructing airports, underground tunnels, gigantic waterfronts, highways, dams and related structures, large-scale irrigation and drainage networks, … etc., the demand for building materials has increased dramatically. Meanwhile, due to the increasing number of civil projects requiring adequate land, many engineers are now thinking about the necessity to build on even lands of swelling-prone compacted soils. Widely distributed all over the world, swelling-prone soils have been seen to be sources of large damages to projects and structures (Sabat, 2012). Swelling behaviour is usually exhibited by the type of clay minerals. At some sites, there are different types of soils in the horizontal and lateral directions (Hashemi Jokar et al., 2019a; Hashemi Jokar et al., 2021; Hashemi Jokar et al., 2019c), which necessitates to determine the type of soil, whether the soil is swelling or not, to prevent heterogeneous settlement (Mirassi and Rahnema, 2020; Rahnema et al., 2021). The tendency of swelling soils to absorb water changes in natural soil moisture. This is due to moisture absorption from groundwater, leakage, moisture caused by watering plants around the structure or local-climate changes. Therefore, this change can lead to an increase in soil water content, possibly to the point where the soil reaches its plastic limit, followed by a loss of water content which leads to a water content below the shrinkage limit. Volumetric changes caused by variations in the soil moisture content induce damages to surface structures. Considering low burden of light structures, such changes may lift the floor and

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sometimes, duct casings and road pavements or establish some cracks on the bottom of slabs, building walls, … etc. Foundations built on such type of soils may suffer from strong interaction forces caused by swelling making lifts, cracks or fractures into foundation components and slabs (Bell, 1993). However, if the swelling force is not that great, here will be cracks and fractures, eventually leading to system damage if not properly maintained and repaired throughout the time. Soil swelling potential (%) is one of the most important steps in the course of foundation design, so soils at risk of swelling must be identified to assess the degree of swelling. In order to evaluate swelling, as proposed by different researchers, there are various direct and indirect experimental methods as well as field approaches in the literature (Erzin and Erol, 2004). In most of the direct evaluation methods, oedometer tests are undertaken; such tests are, however, time-consuming (Hashemi Jokar et al., 2017; Rahnema and Mirassi, 2016; Tu, 2015). As such, there is a need to develop models capable of predicting the swelling with the available experimental data with no swelling tests required. Recently, ANFIS has been employed to solve more complex non-linear problems than those dealt with in geotechnical engineering applications.

Provenzano et al. (2004) used ANFIS to predict foundation behaviour. Their proposed ANFIS model was utilized to simulate responses of foundations under centric and eccentric loadings. The obtained results motivated researchers to use ANFIS for optimizing the proposed experimental model and procedure. Zounemat-Kermani et al. (2009) had their studies on the estimation of current-induced scour depth around pile groups using ANFIS, so as to present an accurate estimation of maximum scour depth around foundations of bridges which are mostly founded on groups of piles. Kayadelen et al. (2009) have employed ANFIS to propose an estimation model for the swelling of compacted soils. They further developed their modeling approach by the use of the grid-partitioning method. Pradhan et al. (2010) proposed landslide susceptibility maps developed *via* ANFIS modeling to demonstrate power and usefulness of the proposed ANFIS model in the course of determining landslide potential. Sezer et al. (2010) presented a model to predict permeability through sand utilizing an ANFIS-based approach. Their model possesses high potentials in terms of providing accurate predictions of sand permeability to be used by geotechnical engineers. Cabalar et al. (2012) modelled damping ratio and shear modulus *via* ANFIS. Based on the obtained data from the resonance column test undertaken by Stokoe, this model gave damping ratio and shear modulus of sand mixtures with coarse grain micas. Hashemi Jokar and Mirasi (2017) used ANFIS to predict unsaturated soils' shear strength. They compared the ANFIS results with those of the empirical models and indicated that ANFIS has a high capability of predicting shear strength compared to empirical model results. Using ANFIS, Hashemi Jokar et al. (2019b) predicted the permeability of unsaturated soil and optimized the number of ANFIS training epochs and ANFIS structure using the trial-and-error method. They could successfully imply the optimum ANFIS to predict the permeability with the best running time and training dataset to generate the ANFIS model. In this paper, two clustering methods; namely, subtractive and fuzzy c-means, were used to generate the fuzzy inference system and the model trained with ANFIS to predict the swelling of compacted soils with an optimum and suitable ANFIS structure.

Adaptive Neuro-Fuzzy Inference System (ANFIS)

Fuzzy logic was first introduced by Lotfi Zadeh in 1965 (Rahnema et al., 2019). It is a flexible and rather easy means to model complex systems *via* mathematical and classical approaches, even in problems impossible or extremely difficult to undertake. In contrary, the classical logic (where an element either is or is not a member of the set; i.e., membership follows a Boolean pattern) with its requirements might seem to have access to accurate quantitative data. Expanding this concept, fuzzy-logic theory introduces the concept of membership degree (Rahmani and Seyed-Hosseini, 2021; Yugendar and Ravishankar, 2019), where an element may be a member of a set to a degree ranging between 0 and 1. This theory is able to mathematically configure many inaccurate ambiguous systems (as the most real-world systems are), so as to make a basis for reasoning, inference, control and decision-making under uncertain conditions. Fuzzy logic serves as a good approach for systems with high uncertainty and complexity. It starts with determining a set of "if – then" rules. Being trainable by various training patterns, artificial neural networks can establish well-suited relationships among different input and output variables. As such, with its ability to use available numerical data to forecast the results, a combined approach with artificial neural networks incorporated into a fuzzy system serves as a powerful tool commonly referred to as ANFIS (Rahnema et al., 2019). In this combined approach, the fuzzy part of the relationship between input and output variables is established with the characteristics of membership functions associated with the fuzzy part being determined using a neural network. Figure 1 shows the structure of ANFIS (Chang and Chang, 2006). As the figure reveals, ANFIS is composed of 5 layers described as follows:

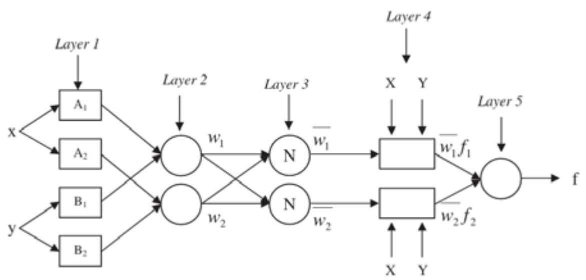


Figure (1): ANFIS structure (Chang and Chang, 2006)

First Layer

This layer includes input nodes with each node being a fuzzy set with its output being the membership degree of the corresponding input variable.

Second Layer

This layer encompasses rule-related nodes with each node in this layer calculating the degree of activity for the corresponding rule.

Third Layer

This layer includes average nodes calculating the ratio of the degree of activity of a rule to the sum of degrees of activities for all rules.

Fourth Layer

Result nodes are established in this layer, where node output is calculated using the results' characteristics.

Fifth Layer

This layer includes output nodes with each node giving the value of the final output (Rahnema et al., 2019).

Database for ANFIS Model

Gathered by Kayadelen et al. (2009), data used to model and predict compacted-soil swelling consists of laboratory datasets obtained from tests on compacted soils. The tests are conducted on the following classes of soils (according to the Unified Soil Classification System (USCS)): high-plasticity clay (CH), low-plasticity clay (CL), intermediate-plasticity clay (CI), clayey gravel (GC), silty gravel (GM), high-plasticity silt (MH), low-plasticity silt (ML) and intermediate-plasticity silt (MI). With the results reported in terms of a total of 98 series of data, the following parameters are measured in laboratory tests: fine-grained fraction ratio (FG), coarse-grained fraction ratio (CG), plasticity index ratio (PI), maximum dry density (MDD) and swelling index (S). In Table 1, the range of datasets used for the ANFIS model is represented.

Table 1. The range of datasets used for the ANFIS model

	Inputs				Output
Soil parameter	CG (%)	FG (%)	PI (%)	MDD (kg/cm^2)	S (%)
Minimum	20.500	13.000	7.370	1.431	2.550
Maximum	87.000	79.500	33.260	2.091	19.790

Out of 98 data series (entire dataset), 74 data series (about 75 %) were taken as the model training dataset (used to train the model, so that input data and output data are directly fed into the model), 9 data series (about 10 %) were taken as the model-checking dataset (used to check and prevent overfitting through training procedure model, so that input data and output data are directly fed into the model), while the remaining 15 data series (about 15 %) served as the model-testing dataset (with which the model has dealt for the first time, such that only input data is fed into the model and output data is to be predicted by the model). In order to prepare the optimum set of data for either training, checking or testing the model, a random approach was followed to put data series in either training, checking or testing datasets. In this way, maximum accuracy and highest predictability can be included in the model, so as to provide an acceptable level of accuracy when using the model.

Development of ANFIS Model to Predict Swelling

In order to predict swelling by ANFIS, it is possible to begin with establishing the corresponding fuzzy inference system (FIS) using the training dataset before it gets further trained by ANFIS and finally validated and assessed by the checking and testing datasets. Therefore, as the first step, training, checking and testing datasets were established by a random fashion. In the next step, training dataset was used along with Takagi-Sugeno model to establish an initial FIS structure using two clustering methods: fuzzy c-means clustering and subtractive clustering. In the following sub-sections, these two methods are introduced.

Fuzzy C-means Clustering

Content fuzzy c-means clustering (FCMC) was introduced by Dunn (1973) and Bezdek (1981). In this method, at first, the number of clusters (NC) should be defined and the cluster centers can be calculated by minimizing the objective function as follows:

$$J_m = \sum_{i=1}^{n} \sum_{j=1}^{c} u_{ij}^{m} \left\| y_i - c_j \right\|^2, \qquad (1)$$

where y_i is the i^{th} data point, c_j is the j^{th} center of the cluster (Eq. (2)), m is a weighting exponent (m=2 (Bezdek 1981)), $\|\,.\,\|$ is the Euclidean distance and u_{ij} is the membership degree (Eq. (3)).

$$c = \frac{\sum_{i=1}^{n} u_{ij}^{m} * y_i}{\sum_{i=1}^{n} u_{ij}^{m}}, \qquad (2)$$

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{\| y_i - c_j \|}{\| y_i - c_k \|} \right)^{\frac{2}{m-1}}}, \qquad (3)$$

As a criterion value to stop clustering, ε, the clustering process will be finished when Eq. (4) is fulfilled:

$$max\left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right\} < \varepsilon. \qquad (4)$$

Determination of NC is one of the most important steps in the FCMC. Therefore, it was focused on finding the best NC in the FCMC.

Figure 2 represents NC *vs.* RMSE resulting from the FCMC created for compacted-soil swelling data. It is obvious that the best range for the FCMC-NC is 60 < NC < 73, where RMSE has the lowest values.

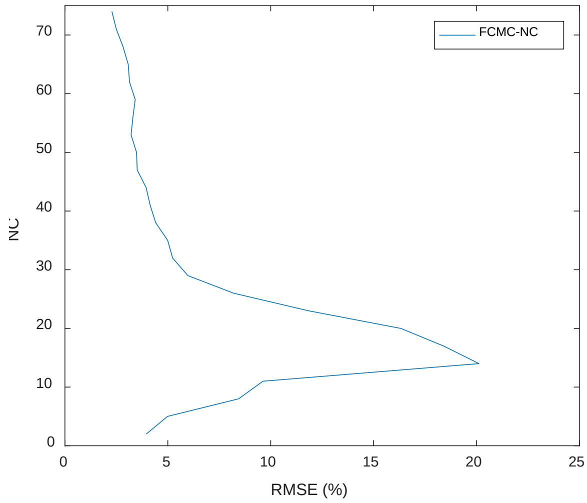


Figure (2): The fuzzy c-means clustering (FCMC) number of clusters (NC), FCMC-NC, *vs.* RMSE

Subtractive Clustering

Subtractive clustering (SC), which was introduced by Chiu (1994), determines the suitable number of clusters needed for the data to be clustered in. This method is a fast, robust and accurate algorithm that gives the possibility of each data point to be a cluster center (p_i). This possibility is calculated by the following equation:

$$p_i = \sum_{j=1}^{n} e^{-\alpha \| x_i - x_j \|^2}, \qquad i = 1, 2, \ldots, n \qquad (5)$$

where n is the number of data points, x_i and x_j are normalized data point and α is:

$$\beta = \frac{4}{NR^2}, \qquad (6)$$

where NR is the neighborhood radius having values between 0 and 1.

As can be seen in Eq. (5), the value of p_i strongly depends on the Euclidean distance between x_i and x_j (which is dependent on the existing dataset and is not possible to change) and the NR value (where it is possible to choose different values, leading to get different numbers of the clusters). In the SC, the goal is to select the best NR to create the best initial FIS for the training. The best NR is determined by plotting NR (0.1 < NR < 1) and the number of clusters (NC) *vs.* RMSE, Figure 2. As can be seen in this figure, for 0.1 < NR < 0.2 (which is corresponding to 55 < NC < 68), RMSE has the lowest values and this range can be used as the best values for NR.

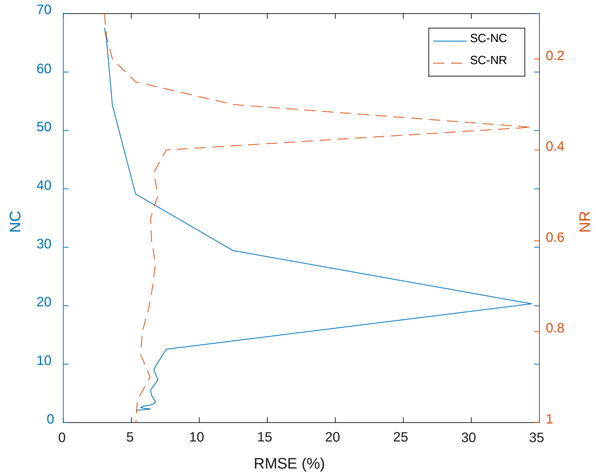


Figure (3): The subtractive clustering (SC) neighbourhood radius (NR), SC-NR and number of clusters (NC), SC-NC, *vs.* RMSE

RESULTS AND DISCUSSION

After finding the optimum FCMC-NC and SC-NR, it is turn to create the initial fuzzy inference system by using FCMC and SC. Therefore, the data was randomly separated into three subsets (training, checking and testing) and the FCMC and SC initial fuzzy inference systems were generated. Once the initial fuzzy inference system was established, the model may be subject to training by ANFIS. Using the least square method and the gradient descent approach, training errors were reduced, so as to well train the model in this step. In the following part, the details of each ANFIS model are presented.

The final ANFIS models for the FCMC and SC methods came with NF of 67 and 70 (corresponding to NR 0,125), respectively, with the selected membership function being a Gaussian function. Further properties of initial fuzzy inference system are reported in Table 2.

Figure 4 shows the initial FIS to predict swelling for both FCMC and SC ANFIS models. Input parameters used to establish this model include FG, CG, PI and MDD with the model output being the swelling percentage S (%).

Table 2. Characteristics of the proposed ANFIS model to predict swelling

Fuzzy type	Sugeno
And method	prod
Or method	probor
Imp method	min
Agg method	max
Defuzz method	wtaver

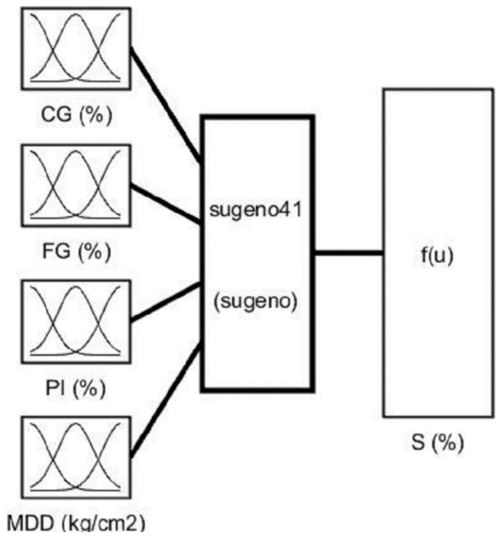


Figure (4): Initial FIS established for swelling-prediction model

Once established, ANFIS models should be analyzed in terms of their performance in estimation and prediction. To this aim, various performance indices including RMSE, MAE and R are used in this study. RMSE and MAE represent errors within the model, so as they are desired to be zero. Being a dimensionless measure, the coefficient of determination (R) ranges from 0 (no correlation between the predicted and the actual values) and 1 (the predicted values are correlated to the actual values), with its best value being 1. The following relationships were used to calculate RMSE, MAE and R:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_{im}-x_{ip})^2}{n}}, \tag{7}$$

$$MAE = \frac{\sum_{i=1}^{n}|x_{im}-x_{ip}|}{n}, \tag{8}$$

$$R^2 = \frac{\sum_{i=1}^{n} x_{im}x_{ip}}{\sqrt{\sum_{i=1}^{n} x_{im}{}^2 \sum_{i=1}^{n} x_{ip}{}^2}}, \tag{9}$$

where X_K and Y_K denote measured and predicted values, respectively, while K stands for the number of data points.

Comparison of predicted S and measured S for both FCMC and SC ANFIS models is presented in Figure 5 for the training, checking and testing subset data. For the sorted 98 data series, the results are shown in Figure 6.

As can be seen in Figure 5, for the whole dataset, predicted S and measured S are matched well for both ANFIS models. There is just a small difference for the checking and testing datasets.

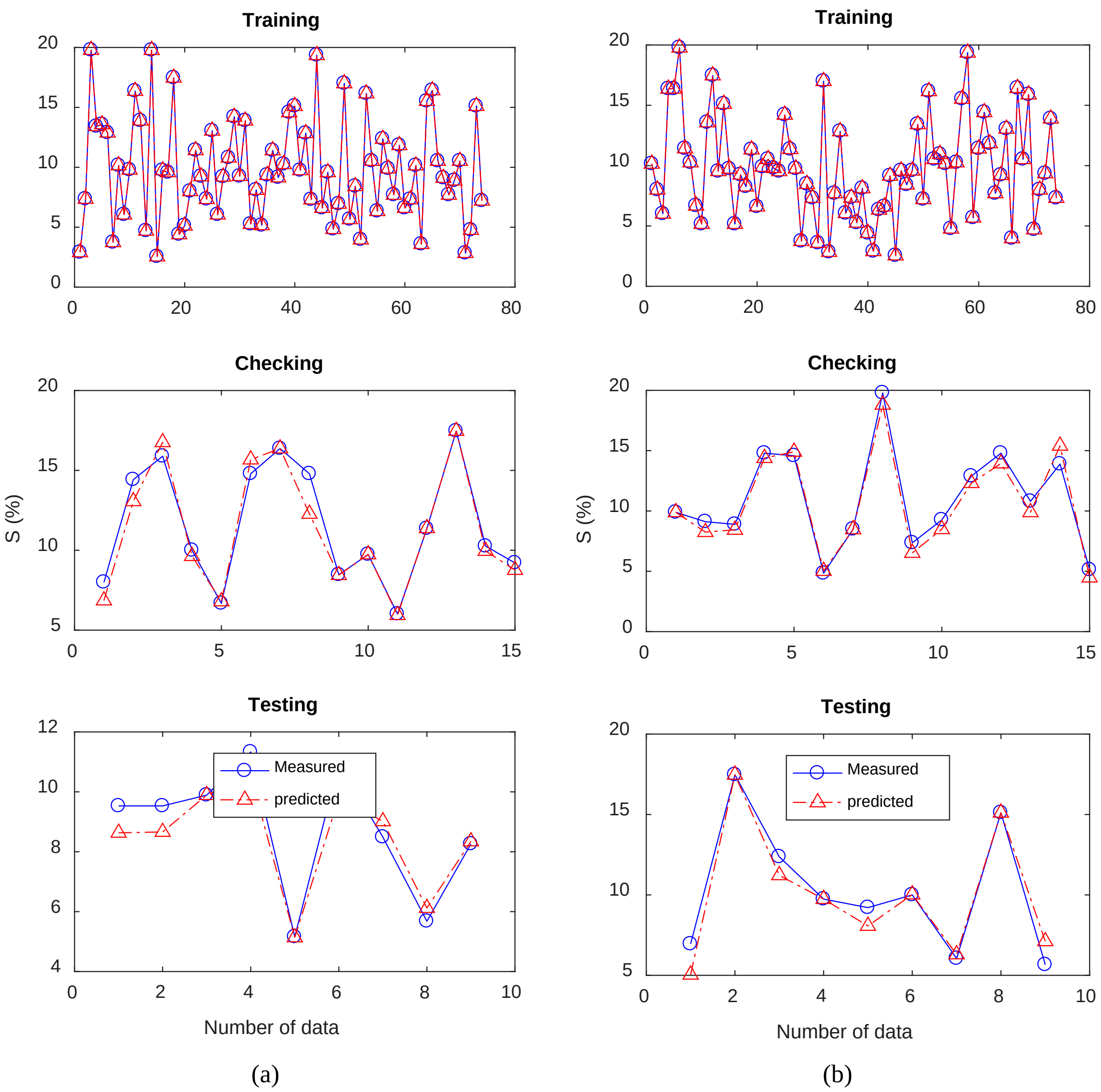
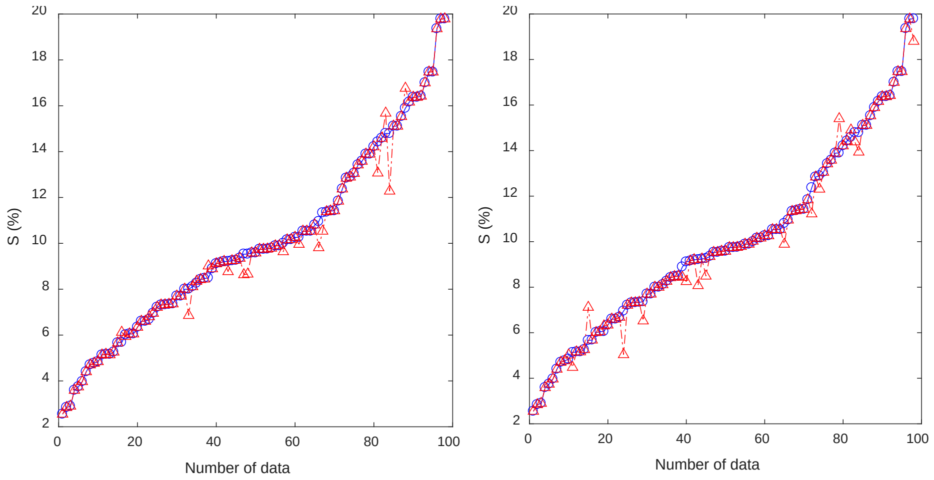


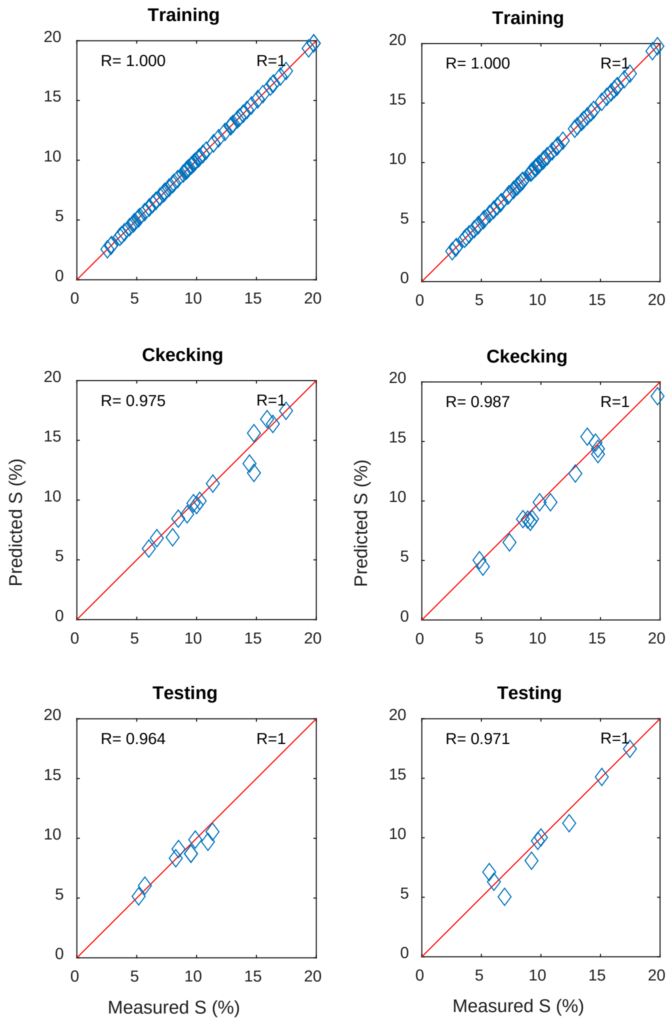
Figure (5): Comparison of predicted S and measured S for the training, checking and testing subset data: (a) FCMC ANFIS model and (b) SC ANFIS model

Output results of swelling-prediction model *vs.* laboratory-measured data for the FCMC and SC ANFIS models are presented for training, checking and testing datasets in Figure 7 and for the whole dataset, the results are shown in Figure 8. Furthermore, the line R = 1 is drawn in these figures. The R value for the SC ANFIS model was greater and closer to 1 in comparison with that of the FCMC ANFIS model. To show better these differences, the values of RMSA, MAE and R for the proposed ANFIS models and the model by Kayadelen et al. (2009) are summarized in Table 3. As seen from the R values, both ANFIS models were compared with the Kayadelen et al. (2009) model and presented good predictions of S values; however, the SC ANFIS model yielded a relatively better prediction than that of the FCMC ANFIS model.



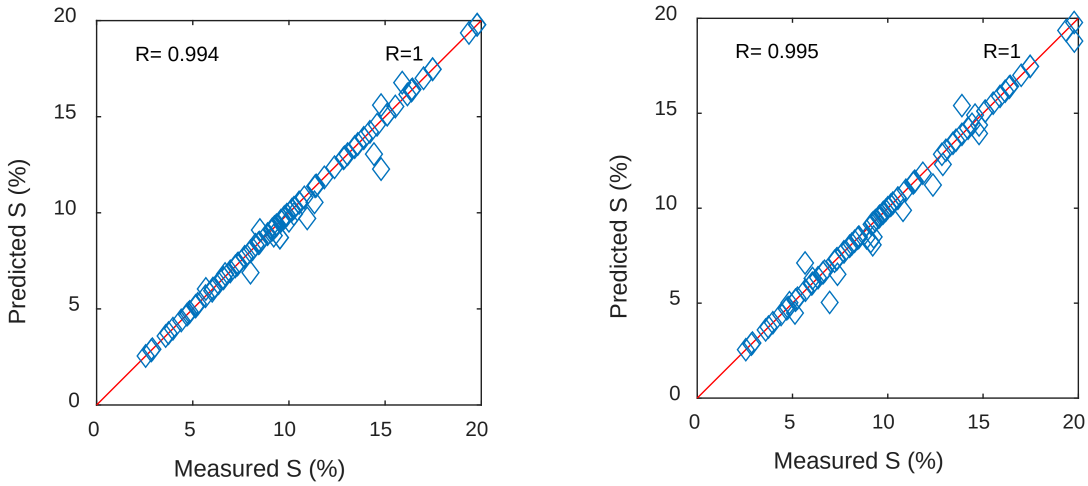
(a) (b)

Figure (6): Comparison of predicted S and measured S for the sorted whole dataset: (a) FCMC ANFIS model and (b) SC ANFIS model



(a) (b)

Figure (7): Measured S *versus* predicted S and the line by R=1 for training, checking and testing datasets in (a) the FCMC model and (b) the SC model



(a) (b)

Figure (8): Measured S *versus* predicted S and the line by R=1 for the whole dataset in (a) the FCMC model and (b) the SC model

Table 3. Values of RMSA, MAE and R for the proposed ANFIS model

ANFIS Model / Datasets	Performance indices						
	RMSE (%)		**MAE (%)**		**R**		
	FCMC	**SC**	**FCMC**	**SC**	**FCMC**	**SC**	**Kayadelen et al. (2009)**
Training	0.000	0.000	0.000	0.000	1.000	1.000	0.930
Checking	0.869	0.737	0.538	0.624	0.975	0.987	
Testing	0.668	0.970	0.525	0.659	0.964	0.971	
All data	0.396	0.412	0.131	0.156	0.994	0.995	

CONCLUSIONS

In this paper, the capability of ANFIS in predicting swelling in compacted soils was investigated. The proposed ANFIS models were established with fuzzy c-means and subtractive clustering methods. One of the most important factors to consider when modeling *via* ANFIS is seen to be the proper choice of data to put in each dataset. Random-selection approach was followed to achieve the optimum situation in terms of dividing the entire dataset into the training, checking and testing datasets. Following this approach, while solving the problem several times with different data-division schemes for each run, the optimum training, checking and testing datasets were established. The values of RMSE for the training, checking, testing and entire datasets were obtained to be less than 0.97 % in both ANFIS models. The values of MAE for the training, checking and testing datasets and the entire dataset were obtained to be less than 0.66 % for both ANFIS models. Being close to 0, the values obtained for MAE and RMSE are seen to be satisfactory. Being close to 1, the values of R for the training, checking and testing datasets and the entire dataset were obtained to be 1.000, 0.975, 0.964 and 0.994, for FCMC ANFIS model and 1.000, 0.987, 0.971 and 0.995 for SC ANFIS model, respectively. Overall values obtained for RMSE, MAE and R indicate that the proposed ANFIS models have succeeded to predict compacted soils' swelling at a good level of accuracy. Knowing the input parameters (i.e., FG, CG, PI and MDD which can be easily obtained by simple tests), it is possible to use the proposed model to predict swelling with a good level of accuracy and high efficiency. Therefore, ANFIS models can be used to predict swelling without getting busy with swelling tests and associated issues.

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Conflict of Interests

The authors declare that they have no competing interests with regard to the publication of this article.

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