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Artificial Intelligence Prediction Model for Swelling Potential of Soil and Quicklime Activated Rice Husk Ash Blend for Sustainable Construction

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ABSTRACT

Artificial intelligence (AI) algorithms of adaptive neuro-fuzzy inference system or the adaptive network-based fuzzy inference system (ANFIS) has been deployed to predict the swelling potential (SP) of treated weak soil. The soil was treated with quicklime activated rice husk ash (QARHA) and the prediction efficiency was compared with the previous outcomes of this operation from literature. The need for effective utilization of construction materials to achieve sustainable designs and monitoring of the behavior of built environment is the motivation behind the deployment of artificial intelligence in geo-environmental research and field operations. The use of ANFIS is common in different fields of science and business to predict the best fits from several data points. The results of this modeling exercise conducted with 25 datasets from mixture experimental treatment of soft soil with QARHA has shown that ANFIS is a better tool compared to the individual algorithms of ANN and FL and even the other artificial intelligence tools like scheffe, ANOVA, regression and extreme vertices methods. With performance index of 88% and correlation of about 71% in the ANFIS testing and 17% and 99% respectively in the ANFIS training, ANFIS proved to be a more powerful tool in achieving a more sustainable material utilization in earthwork constructions, design and monitoring of geotechnical systems performance.

Keywords: Soft Computing; Adaptive Neuro-Fuzzy Inference System (ANFIS); Artificial Intelligence (AI); swelling potential; fuzzification; defuzzification; sustainable construction materials

INTRODUCTION

Introduced by Jang, Adaptive Neuro-Fuzzy Inference System (ANFIS) is a Sugeno or Takagi–Sugeno–Kang (TSK) type fuzzy inference system (FIS) incorporating the ANN principles (Sugeno 1985; Venkatesh and Bind 2020; Jyh-Shing 1993). It is a hybrid model system which includes the fuzzy and ANN algorithms (Jang 1983). There are two main limitations of this type of modelling; (i) The models formulated by ANFIS are complex in viewpoint of considered membership functions and if-then rules which form the final output, (ii) they do not adapt and train to a stochastic situation (Mazari and Rodriguez, 2016; Panahi et al. 2020). In ANFIS structure, optimization algorithm is used by training ANFIS in the determination of the two different parameter groups known as premise and consequence. Respectively, gradient descent (GD) and least square estimation (LSE) methods are used to determine the premise and consequence in training ANFIS procedure. To achieve effective results through the selection of the best optimization method utilized in training, derivate- and non-derivate-based algorithms are used in ANFIS training.

However, a hybrid process where the algorithms of derivate- and non-derivate-based ANFIS training has been developed with enhanced functionality and outcome.

In order to deal with the complexity of geotechnical behavior of erratic soils, binder materials and the blend of soils and cementing materials, basic forms of model designs in engineering mathematics are justifiably simplified (K. C. Onyelowe et al. 2019a; 2019b; Onyelowe et al. 2018a; 2018b). Certain empirical and semiempirical approaches are based on the available data alone to determine the structure, validity and applications of the model. The technique known as Adaptive Neuro-Fuzzy Inference System (ANFIS) seems to be suited with success to model complex problems in materials, geotechnical and geo-environmental engineering where the relationship between the model variables is unknown.

An ANFIS model has proven to bring together the elemental and individual representation of a fuzzy logic (FL) system with the learning ability of Artificial Neural Networks (ANNs). With the advancement of recent artificial intelligence (AI) techniques, ANFIS has been recently deployed in the diverse fields of engineering to model the behavior of systems and successful results were recorded. In geotechnical and geo-environmental systems particularly, ANFIS was applied by Cabalar et al. (2011) in conducting an overview its applications in geotechnical engineering, Erdirencelebi and Yalpir (2011) in the prediction of anaerobic digestion effluent quality, Jokar and Mirasi (2017) in the modeling of unsaturated soils shear strength. Also, this evolving field of ANFIS has been applied by Karaboga and Kaya (2019) as a comprehensive review was conducted, by Mohammed et al. (2020) to predict shallow foundation settlement quatification, by Panahi et al. (2000) to predict spatial landslide susceptibility by applying various metaheuristic algorithms, by Venkatesh and Bind (2020) to model the shear strength characterization of soils and it is clearly observed that no recent works have been carried out with ANFIS on the mixture experiments of soils stabilization. The above exercise which deployed the use of ANFIS showed very clear and good correlations that can be useful in the design and monitoring of those systems. However, ANN and FL were also explored in their individual functionalities to predict various systems in geo-environmental engineering applications. These included; prediction of UCS of treated expensive soil by back propagation algorithms of ANN (A. B. Salahudeen, 2020), modelling of swelling potential of quicklime activated rice husk ash treated soft soil by FL method (Alaneme et al. 2020a), modeling volume change of hydrated lime activated rice husk ash modified soft soil by ANN method (Alaneme et al. 2020b), comparative modeling of strength properties of hydrated lime activated rice husk ash modified soft soil by ANN and FL methods (Alaneme et al. 2021), the prediction of UCS and CBR of treated sulfate silty sand with applications to deep soil mixing by using ANN (Ghorbani and Hasanzadehshoiili, 2018) and the prediction of pavement roughness using ANN (Mazari and Rodriguez, 2016). These show that ANN and FL in their individual applications have been pronounced in the field of soil properties modification for sustainable construction while however, the use of ANFIS in this field has not been well utilized to simulate the behavior of soil in blends of cementitious materials. Other fields in engineering have also found application of ANFIS very useful. For instance, in the field of electronic engineering, mobile learning was predicted with the use of ANFIS (Al-Hmouz et al. 2012) and in the field of agriculture a model for the prediction of moisture diffusivity and specific energy consumption potato, garlic and cantaloupe drying under convective hot air dryer was developed with great success and near perfect correlation (Mohammad et al. 2018).

MATERIALS AND METHOD

MATERIALS

Clayey soil with the basic characteristics as presented in Table 1 and Figure 1 was used in this exercise. The QARHA was synthesized by blending pulverized rice husk ash (particle spread of which is presented in Figure 1) and activator materials; quicklime in the ratio of 1:1. The formulated QARHA was then utilized in the treatment of the soil blended in the ratios of 0 to 12% by weight of the soil in increments of 0.5% in accordance with the provisions of British Standard International, BS 1924 (1990). The treatment exercise produced 25 data points from 25 experimental specimens used to study the consistency of the treated soil. The values of the SP were computed with the PI method proposed by Chen (1988) and the results are presented in Table 2.

TABLE 1. Particle size distribution (PSD) of test materials

Soil property	%passing no. 200 sieve	NMC	LL	PL	PI	SP	AASHTO	MDD	OMC	DoE
value	45	14	66	21	45	23	A-7-6	1.25	16	High

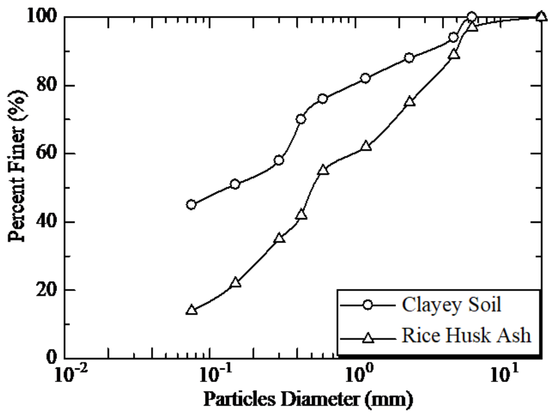


FIGURE 1. Particle size distribution curve of the clayey soil and rice husk ash

TABLE 2. 25 data points of consistency and swelling potentials of QARHA treated clayey soil

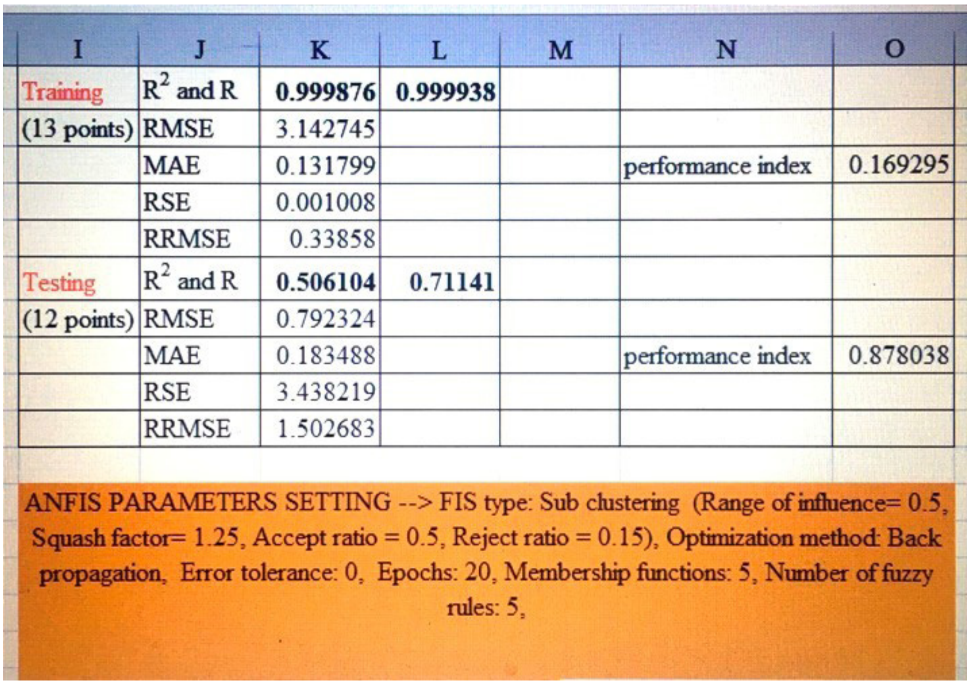
QARHA (%)	Swelling Properties			
	LL (%)	PL (%)	PI (%)	SP Actual (%)
0	66	21	45	23.35
0.5	63	21	42	19.7
1	61	21	40	17.5
1.5	58	20.5	37.5	15
2	55	20	35	12.7
2.5	51	19.5	31.5	9.8
3	49	19	30	8.7
3.5	47	19	28	7.3
4	43	19	24	5
4.5	40	18	22	4.1
5	37	18	19	2.9
5.5	34	18	16	1.9
6	31	18	13	1.1
6.5	29	17	12	0.9
7	27	17	10	0.6
7.5	26	16	10	0.6
8	25	15	10	0.6
8.5	25	15	10	0.6
9	25	15	10	0.6
9.5	24	14	10	0.6
10	24	14	10	0.6
10.5	23	14	9	0.5
11	23	14	9	0.5
11.5	22	14	8	0.3
12	21	13	8	0.3

METHODS

The 25 experimental outcomes were deployed into ANFIS model to generate the swelling potential model presented in Table 3. 13 datasets and 12 datasets out of the entire datasets of the present exercise were deployed for ANFIS training and testing as presented in Figure 2. This was achieved by using a sub-clustering fuzzy inference system type, with 0.5 influence range and squash factor of 1.25 under back propagation optimization method.

TABLE 3. SP ANFIS Model Outcome

Datasets	SP Actual	SP ANFIS Model
1	23.35	22.8571362
2	19.7	19.23541515
3	17.5	17.06740995
4	15	14.81850471
5	12.7	12.63473257
6	9.8	9.763428388
7	8.7	8.689836504
8	7.3	7.292190707
9	5	7.292190707
10	4.1	4.099610915
11	2.9	2.89987792
12	1.9	1.899941047
13	1.1	1.099972801
14	0.9	1.047075612
15	0.6	0.457477664
16	0.6	0.632519788
17	0.6	0.799213899
18	0.6	0.802027
19	0.6	0.803839626
20	0.6	0.963802752
21	0.6	0.964350854
22	0.5	0.646759729
23	0.5	0.646941234
24	0.3	0.329035056
25	0.3	0.487358041



I	J	K	L	M	N	O
Training	R^2 and R	**0.999876**	**0.999938**			
(13 points)	RMSE	3.142745				
	MAE	0.131799			performance index	0.169295
	RSE	0.001008				
	RRMSE	0.33858				
Testing	R^2 and R	**0.506104**	**0.71141**			
(12 points)	RMSE	0.792324				
	MAE	0.183488			performance index	0.878038
	RSE	3.438219				
	RRMSE	1.502683				

ANFIS PARAMETERS SETTING --> FIS type: Sub clustering (Range of influence= 0.5, Squash factor= 1.25, Accept ratio = 0.5, Reject ratio = 0.15), Optimization method: Back propagation, Error tolerance: 0, Epochs: 20, Membership functions: 5, Number of fuzzy rules: 5,

FIGURE 2. SP ANFIS model training and testing parameters setting interface

DISCUSSION OF RESULTS

Five membership functions and five number of fuzzy rules were considered. Various ANFIS parameter settings are given in Table 4. The data comprising geotechnical properties of stabilized clay soil was employed to formulate and develop the ANFIS model while assessing the swell potential of the QARHA-Soil mixture. Different dosage level of QARHA, untreated expansive clay, liquid and plastic limits were fed to the ANFISEDIT network in MATLAB R2020b in the form of predictor variables whereas the swelling potential of treated soil is considered as the output variable (see Figure 3). The fuzzy variables were assigned a unique degree of membership based on expert judgment and details from the system data base.

TABLE 4. ANFIS parameter settings

Parameter	Setting
FIS type	Sub clustering
Range of influence	0.5
Squash factor	1.25
Accept ratio	0.5
Reject ratio	0.15
Optimization method	Back propagation
Error tolerance	0
Epochs	20
Membership functions	5
Number of fuzzy rules	5

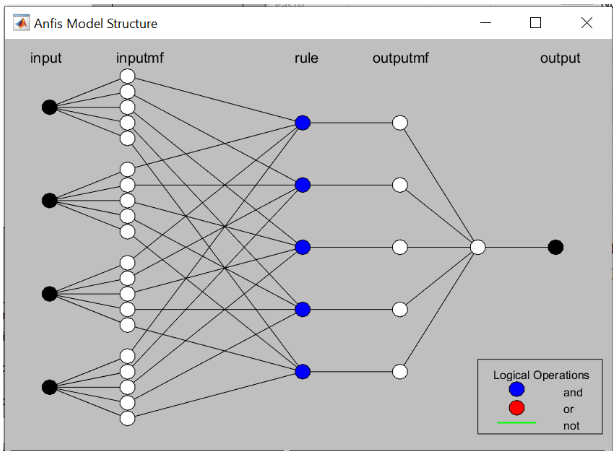


FIGURE 3. ANFIS Architecture for SP 25 input datapoints

For optimizing the given experimental values, the training and testing datasets were fed in the ANFIS model for estimation of swell potential. As seen in Table 5, the overall correlation coefficient R is 99% and 51% for training and testing data set of swell potential which indicates strong predictive ability of the model. As evident from the Figure 4, the difference in these coefficients is attributed to the drawback of model overfitting that is generally encountered in ANFIS.

TABLE 5. Training and testing data sets performance

Training data set	R2	0.999
	R	0.999
	RMSE	3.142
	MAE	0.131
	RSE	0.001
	RRMSE	0.338
	P. I	0.169
Testing data set	R2	0.506
	R	0.711
	RMSE	0.792
	MAE	0.183
	RSE	3.438
	RRMSE	1.502
	P. I	0.878

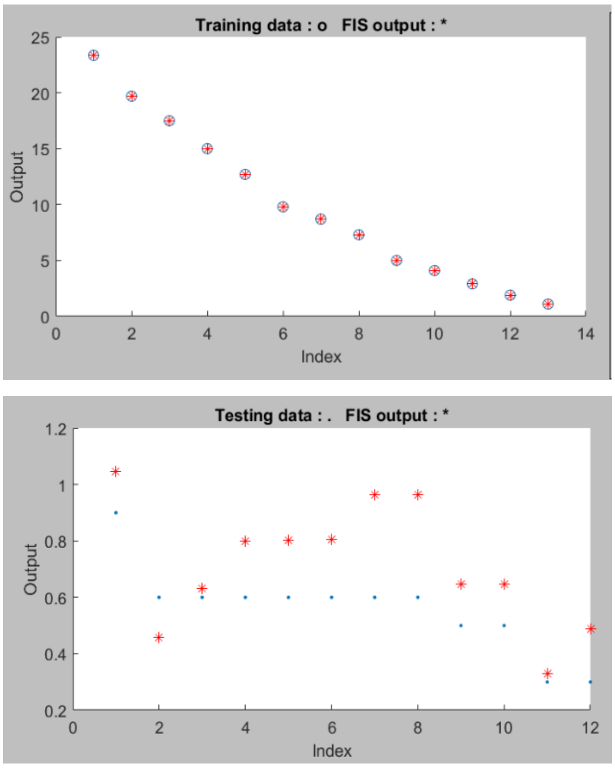


FIGURE 4. Fuzzy inference system output raining and testing datasets performance and behavior

The magnitude of errors i.e. Mean Absolute Error (MAE), Root Squared Error (RSE), Nash-Sutcliffe Efficiency (NSE), and Root Mean Squared Error (RMSE) are lower, while Performance Index (P.I) values are 0.169 and 0.878, for both training and testing dataset, respectively. The closer value to 0 represents higher efficacy of the respective model. The ANFIS model can effectively be incorporated for the estimation of swell potential of QARHA-Soil mixture. The effect of LL, PL and PI on the swell potential of treated expansive soil is graphically shown in the Figure below, where, the LL first decreases and then rises sharply, the PL follows a decreasing trend whereas the PI indicates an increasing trend and later reduces smoothly with the predicted output variable in ANFIS modelling.

PARAMETRIC STUDY OF ANFIS MODEL

In order to investigate the effects of QARHA addition, along with other variables on swell potential of the expansive soil yielded from the ANFIS model, the output 3D plots of the model were plotted which are illustrated in Figure 5. In the 1st graph, the impact of QARHA alongside an extra variable on the swell potential is portrayed in the 3D plot. As can be observed, the swell potential increases up to 7.5% for untreated expansive soil while it is decreased to around 2% at QARHA of 6%, while the LL has slight effect on the change in swell potential and the SP is found to decrease with LL. In the 2nd figure, the increase in plastic limit increases the swell potential until 19.5% but after that the SP is recorded to plummet with further increase in plastic limit value. In Figure 3, the PI is directly related to the swelling potential and approaches 25% at PI of 25%, while with increasing QARHA the SP is observed to decrease to as low as 12%.

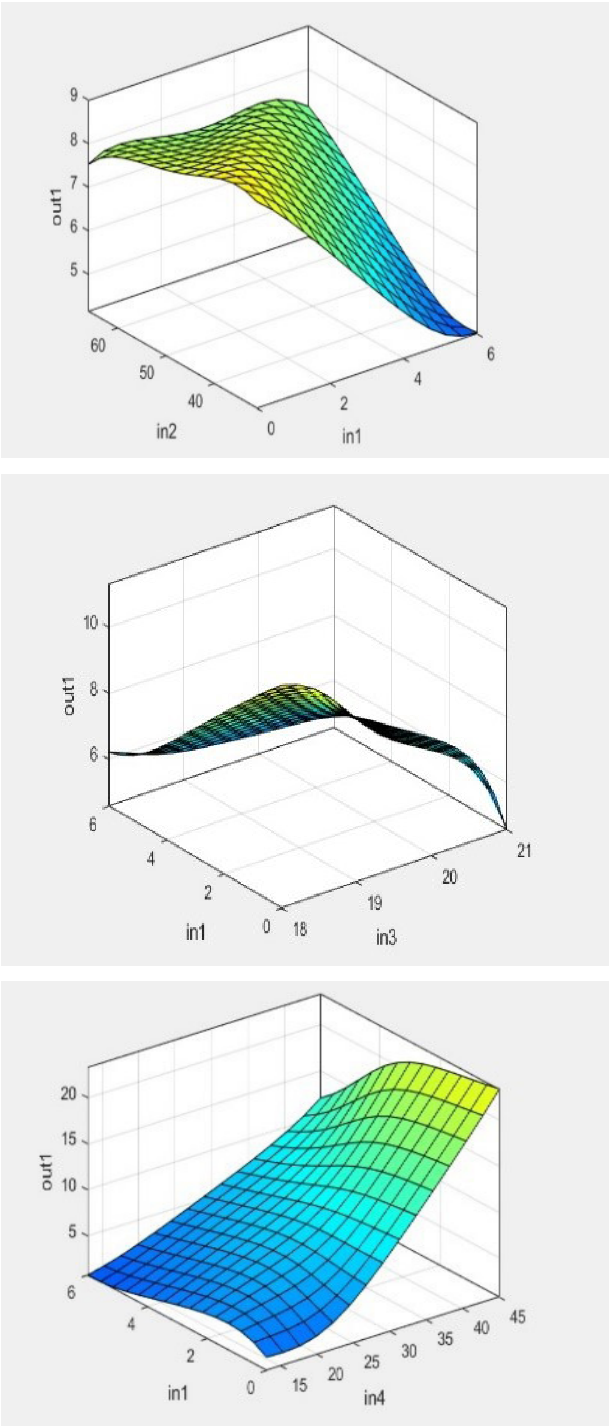


FIGURE 5. Parametric study of the variables' effects on swell potential of the treated expansive soil from ANFIS model

CONCLUSION

ANFIS has been used with great efficiency and response to predict with near perfect correlation, the swelling potential of QARHA treated soil in this work. This hybrid technique has shown with 99% clarity the gradual change in the swelling potential of the treated soil with the proportionate addition of the admixture. The results show better correlation in terms of performance than the individual applications of ANN and FL and of course other artificial intelligence tools like scheffe, extreme vertices, analysis of variance and regression methods applied in civil engineering. ANFIS as a sustainable technology, has not only shown the data points with high performance index but has proven as a tool for sustainable utilization of construction materials in a stabilization protocol and the monitoring of the behavioral changes in the properties of treated materials in an earthwork. Generally, ANFIS has shown to be a perfect tool for geo-environmental designs, construction and system performance observation for the 21st century.

DEFINITION OF TERMS

ANFIS	Adaptive Neuro-Fuzzy Inference System
FIS	Fuzzy Inference System
MAE	Mean Absolute Error
RSE	Root Squared Error
NSE	Nash-Sutcliffe Efficiency
RMSE	Root Mean Squared Error
P. I	Performance Index
QARHA	Quicklime activated rice husk ash
SP	Swelling potential
PI	Plasticity index
LL	Liquid limit
R	Correlation coefficient

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DECLARATION OF COMPETING INTEREST

None

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