www.dergipark.gov.tr
ISSN:2148-3736
El-Cezerî Fen ve Mühendislik Dergisi
Cilt: 9, No: 4, 2022 (1255-1264)

El-Cezerî Journal of Science and Engineering
Vol: 9, No: 4, 2022 (1255-1264)
DOI : 10.31202/ecjse.1133184

ECJSE

Research Paper / Makale

Prediction of the Shear Strength of Glass Fiber-Reinforced Clay Soil by Adaptive Neuro-Fuzzy Inference System (ANFIS)

Ahmetcan SUNGUR[a]*, Mehmet Fatih YAZICI[b], Sıddıka Nilay KESKİN[c]

[a]Department of Civil Engineering, Graduate School of Natural and Applied Sciences, Suleyman Demirel University, Isparta, Turkey, 100/2000 YOK PhD Boursier
[b,c]Civil Engineering Department, Suleyman Demirel University, Isparta, Turkey
ahmetcansungur@gmail.com

Received/Geliş: 20.06.2022 **Accepted/Kabul:** 15.09.2022

Abstract: The objective of this study is to estimate the shear strength of glass fiber reinforced clay soil using ANFIS. For this purpose, specimens with different water contents (13%, 15% and 17%) and different glass fiber addition ratios (0%, 1%, 1.5% and 2%) were prepared. The ANFIS models were created using the shear strength (τ) data obtained by direct shear tests on the prepared specimens. To create the best fitting ANFIS model in the current study, 75%, 77%, 80%, and 83% of the data for training and 25%, 23%, 20%, and 17% of the data for testing were used, respectively. However, to estimate the shear strength in each ANFIS model, the normal stress (σ), glass fiber content (F_c), and water content (ω) are considered as input parameters. Statistical parameters such as root mean square error (RMSE), regression coefficient (R^2), root square error (RSE), and mean absolute error (MAE) were also calculated to determine the success rates of the ANFIS models. Examination of the statistical parameters revealed that the data used 80% for training and 20% for testing provided the best results in estimating the shear strength of the ANFIS model.

Keywords: Artificial intelligence algorithms, ANFIS, shear strength, glass fiber, soil reinforcement

Cam Fiberle Güçlendirilmiş Killi Zeminin Kayma Mukavemetinin Uyarlamalı Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS) ile Tahmini

Öz: Bu çalışmada, ANFIS ile cam fiberle güçlendirilmiş killi zeminin kayma mukavemetlerinin tahminleri amaçlanmıştır. Bu amaç için, farklı su içeriklerine (%13, %15 ve %17) ve farklı cam lifi katkı oranlarına (%0, %1, %1,5, ve %2) sahip deney numuneleri hazırlanmıştır. Hazırlanan numuneler direkt kesme deneyine tabi tutularak elde edilen kayma mukavemeti (τ) verileri kullanılarak ANFIS modelleri oluşturulmuştur. Mevcut çalışmada en uygun ANFIS modelini oluşturabilmek amacıyla, sırasıyla %75, %77, %80 ve %83 eğitim, %25, %23, %20 ve %17 oranında veri test için kullanılmıştır. Bununla birlikte her bir ANFIS modelinde kayma mukavemetini tahmin edebilmek için, normal gerilme (σ), cam lifi miktarı (F_c) ve su içeriği (ω), girdi parametreleri olarak dikkate alınmıştır. Ayrıca, ANFIS modellerinin başarı oranlarını belirleyebilmek için ortalama karesel hatanın karekökü (RMSE), regresyon katsayısı (R^2), karesel hatanın karekökü (RSE) ve ortalama mutlak hata (MAE) gibi istatiksel parametreler hesaplanmıştır. İstatiksel parametrelerin incelenmesi sonucunda %80 eğitim ve %20 oranında test için ayrılan verilerin ANFIS modelinin kayma mukavemeti tahmininde en iyi sonuçları verdiği gözlemlenmiştir.

Anahtar Kelimeler: Yapay zeka algoritmaları, ANFIS, kayma mukavemeti, cam lif, zeminlerin güçlendirilmesi

How to cite this article
Sungur, A., Yazıcı, M.F., Keskin, S.N., "Prediction of the Shear Strength of Glass Fiber-Reinforced Clay Soil by Adaptive Neuro-Fuzzy Inference System (ANFIS)" El-Cezerî Journal of Science and Engineering, 2022, 9(4); 1255-1264.

Bu makaleye atıf yapmak için
Sungur, A., Yazıcı, M.F., Keskin, S.N., "Cam Fiberle Güçlendirilmiş Killi Zeminin Kayma Mukavemetinin Uyarlamalı Ağ Tabanlı Bulanık Çıkarım Sistemi (ANFIS) ile Tahmini" El-Cezerî Fen ve Mühendislik Dergisi 2022, 9(4); 1255-1264.
ORCID ID: [a]0000-0001-6200-7601; [b]0000-0002-3557-7817; [c]0000-0002-0367-943X

1. Introduction

One of the most important issues in geotechnical engineering is the nature of the soil on which the structure is to be built. The soil must be capable of safely supporting the structure to be built. However, problematic soils are often encountered in the areas where the structures are to be erected. In such cases, various reinforcement methods are used to reduce the permeability of problem soils, reduce liquefaction potential, improve absorption, swelling, and settlement properties, and increase shear strength. One of these solution methods is the reinforcement of soils with randomly distributed discrete fibers [1]. In the literature, many researchers have conducted studies using randomly distributed discrete fibers to increase the shear strength of soils [2-5]. The shear strength value of soils can be determined by the direct shear test, uniaxial compression test, triaxial compression test, etc. in laboratories. However, these tests can be complicated, expensive, and time-consuming depending on the type of test. Therefore, artificial intelligence algorithms have been widely used in recent years to solve these complex problems [6-13]. By examining the literature, it was found that artificial intelligence algorithms are useful in estimating the shear strength of soils. Venkatesh and Bind [6] performed the estimation of shear strength parameters (cohesion and internal friction angle) using artificial intelligence algorithms ANFIS and Artificial Neural Network (ANN) models. They also found that ANFIS gave better results compared to ANFIS and ANN. Besalatpour et al. [7] used ANFIS, ANN, and Multiple Linear Regression (MLR) to estimate the shear strength. Jokar and Mirasi [8] worked with ANFIS to determine the shear strength of unsaturated soils. Ding et al. [9] estimated liquid limit, specific gravity, clay content, water content, void ratio, and plastic limits as input parameters and shear strength as output parameters by using ANFIS and Henry Gas Solubility Optimization (HGSO) together.

The objective of this study is to estimate the shear strength of glass fiber reinforced clay soil using an adaptive neuro-fuzzy inference system (ANFIS). There are few studies on glass fiber reinforced soils in the literature. Moreover, no study estimates the shear strength of glass fiber reinforced clay soil using the ANFIS artificial intelligence algorithm. For this purpose, ANFIS models were constructed by Yazıcı et al. [14] using the obtained experimental data. Also, statistical parameters were used to determine the best estimation models in ANFIS models.

2. Material and Method

2.1. Dataset

In this study, to estimate the shear strength of glass fiber reinforced clay soil with low plasticity previously determined by Yazıcı et al. [14], the data whose experimental studies were conducted by the direct shear test is used. In the study conducted by Yazıcı et al. [14], glass fiber material with a length of 6 mm and a diameter of 13-15 μm was used to reinforce the soil. To investigate the effects of glass fiber reinforcement on the shear strength parameters of clay soil, 0%, 1%, 1.5%, and 2% by weight fibers were added to the dry soil. To observe the effects of water content on the fiber-soil mixture, the optimum water content (OWC) and OWC±2 water amounts were used in this study. First, the appropriate amount of fiber glass material was added to the previously oven-dried soil and mixed. Then, 13%, 15%, and 17% water were added to this prepared mixture and the mixture was mixed by hand until the fibers were homogeneously distributed in the soil. The samples were prepared by pressing each mixture with the maximum dry weight in a ring with dimensions 60 mm x 60 mm x 20 mm. Each prepared sample was cut at a cutting speed of 1 mm/min under vertical stresses of 60, 120, and 240 kPa in a direct shear test up to a 15% change in length. As a result, 36 different shear strength values were obtained (Figure 1).

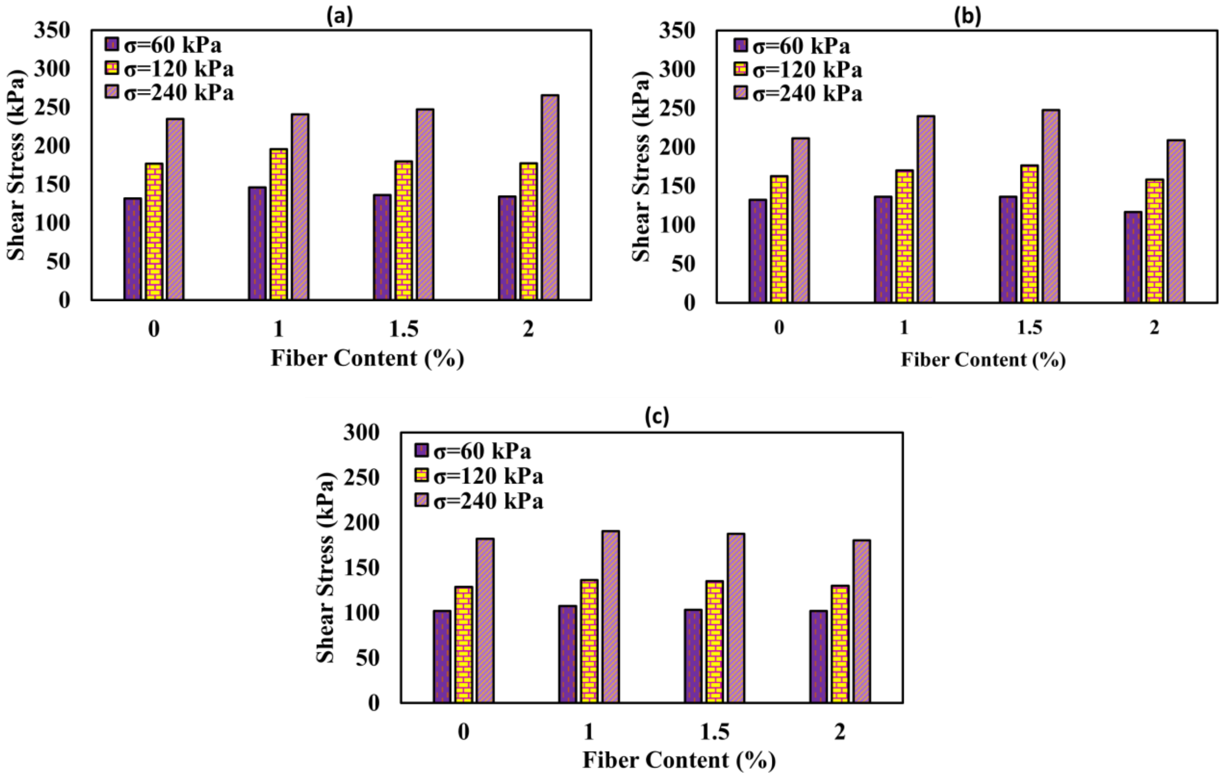

Figure 1. Effect of normal stress (σ) and fiber content (F_c) on shear strength of specimens prepared with (a) 13%, (b) 15%, (c) 17% water content (ω) [14]

2.2. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The applications of artificial intelligence algorithms in the field of engineering are increasing day by day [15,16]. In this study, an adaptive neuro-fuzzy inference system (ANFIS) of artificial intelligence algorithms was preferred. ANFIS was developed by Jang [17] and uses fuzzy logic and artificial neural network learning ability together [18,19]. Therefore, ANFIS is more successful than fuzzy logic and artificial neural network models alone. When the input and output values are known, ANFIS determines all possible rules.

The ANFIS model consists of five different layers. These layers are the fuzzy, product, normalized, de-fuzzy, and total output layers, respectively [20]. The ANFIS architecture is shown in Figure 2.

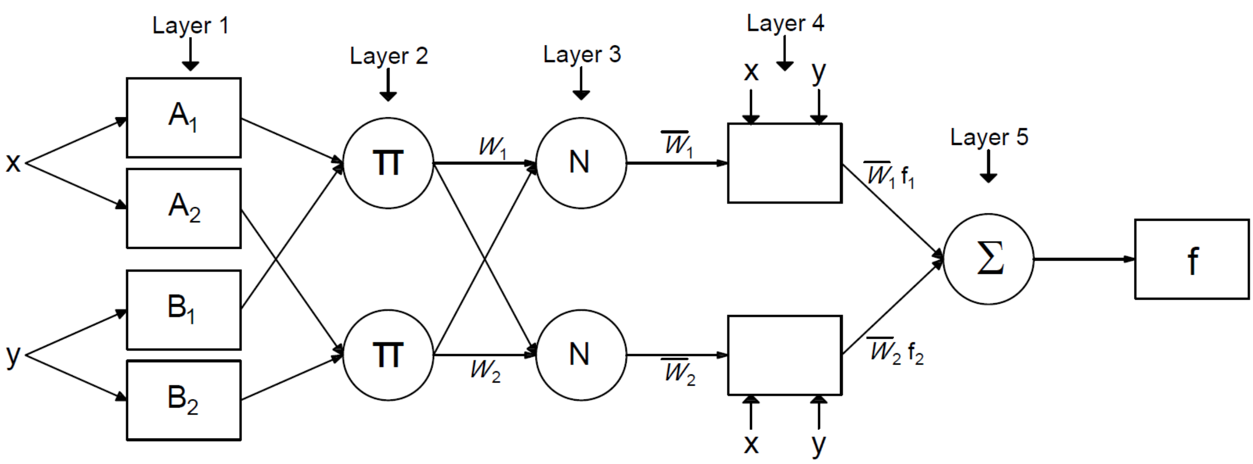

Figure 2. ANFIS architecture

In the study of the ANFIS architecture, the values A_i and B_i are verbal variables in the first layer. The values of A_i and B_i transition to the 2nd layer with membership function and degree of membership. In the second layer, the transition to the third layer is made by applying the multiplication operation. In the third layer, the values are normalized by proportioning. In the 4th layer, the output variable is defined as a fixed number or variable. In the last layer, the total output value of the system is determined [21,22].

When working on ANFIS models, the people creating these models should have both a good command of ANFIS, one of the artificial intelligence algorithms, and sufficient knowledge of the technical area they intend to use. When building ANFIS models, the data used for training and testing and the results to be predicted should be carefully selected. The objective of this study is to estimate the shear strength of fiber-reinforced clay soil using an ANFIS. For this purpose, test specimens were prepared with different water contents (13%, 15% and 17%) and different glass fiber addition ratios (0%, 1%, 1.5% and 2%). The prepared specimens were subjected to a direct shear test to obtain the shear strength values. ANFIS models were prepared from the direct shear test data [14]. The values of the statistical parameters of the data used in the ANFIS models are listed in Table 1. When creating ANFIS models, the data should be separated into training and test data. Due to the small number of data, 75%, 77%, 80%, and 83% of the data for training and 25%, 23%, 20%, and 17% for testing, respectively, were used in the present study to create the most appropriate ANFIS model. For each different training and testing rate, 36 ANFIS models were created, resulting in a total of 144 ANFIS models. The created ANFIS models are also statistical parameters by calculating the root mean square error (RMSE), regression coefficient (R^2), root square error (RSE), mean absolute error (MAE), and standard deviation (SD), skewness coefficient (SC), and kurtosis coefficient. ANFIS models were identified that gave the best results for the shear strength of clay soil reinforced with glass fibers.

Table 1. Values of the statistical parameters of the data used in the ANFIS models.

ANFIS	Variables	Symbol	Unit	Min.	Max.	Mean	SD	SC	KC
75% Train	Normal Stress	σ	kPa	58.07	242.25	137.97	75.68	0.37	-1.61
	Fiber Content	F_c	-	0.00	2.00	1.11	0.81	-0.35	-1.53
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.61
	Shear Stress	τ	kPa	102.18	265.49	166.98	43.33	0.59	-0.55
25% Test	Normal Stress	σ	kPa	59.43	236.91	137.43	77.67	0.33	-1.81
	Fiber Content	F_c	-	0.00	2.00	1.17	0.56	-0.58	-0.30
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.81
	Shear Stress	τ	kPa	101.94	240.78	171.29	56.65	0.11	-1.82
77% Train	Normal Stress	σ	kPa	58.07	242.25	135.16	75.73	0.42	-1.56
	Fiber Content	F_c	-	0.00	2.00	1.14	0.81	-0.40	-1.49
	Water Content	ω	-	0.13	0.17	0.15	0.02	-0.06	-1.62
	Shear Stress	τ	kPa	101.94	265.49	164.66	44.26	0.57	-0.56

Table 1. Values of the statistical parameters of the data used in the ANFIS models (continue).

23% Test	Normal Stress	σ	kPa	59.57	236.91	147.18	76.91	0.18	-1.92
	Fiber Content	F_c	-	0.00	1.50	1.06	0.50	-0.98	-0.13
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.18	-1.72
	Shear Stress	τ	kPa	103.22	240.78	179.96	53.80	-0.02	-1.83
80% Train	Normal Stress	σ	kPa	58.07	242.25	138.60	76.64	0.34	-1.65
	Fiber Content	F_c	-	0.00	2.00	1.10	0.83	-0.32	-1.58
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.65
	Shear Stress	τ	kPa	101.94	265.49	167.08	45.39	0.48	-0.79
20% Test	Normal Stress	σ	kPa	59.57	236.91	134.64	73.71	0.44	-1.68
	Fiber Content	F_c	-	1.00	1.50	1.21	0.27	0.23	-2.20
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.71
	Shear Stress	τ	kPa	103.22	240.78	172.10	52.92	0.20	-1.73
83% Train	Normal Stress	σ	kPa	58.07	242.25	137.89	75.41	0.37	-1.60
	Fiber Content	F_c	-	0.00	2.00	1.10	0.81	-0.31	-1.54
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.60
	Shear Stress	τ	kPa	101.94	265.49	167.18	44.60	0.49	-0.71
17% Test	Normal Stress	σ	kPa	59.57	236.91	137.54	80.31	0.31	-1.96
	Fiber Content	F_c	-	1.00	1.50	1.25	0.27	0.00	-2.31
	Water Content	ω	-	0.13	0.17	0.15	0.02	0.00	-1.96
	Shear Stress	τ	kPa	103.22	240.78	172.45	57.96	0.17	-1.98

3. Results and Discussion

In the study, MATLAB software was used to analyze the ANFIS models. Root mean square error (RMSE) was used as a criterion for the performance evaluation of the models. In addition, statistical parameters such as the regression coefficient (R^2), root squared error (RSE), mean absolute error (MAE), standard deviation (SD), skewness coefficient (SC), and kurtosis coefficient (KC) were calculated to evaluate the success rates of the models.

The statistical parameters corresponding to the best ANFIS models with RMSE values below 10 are given in separate tables for the training and testing phases (Tables 2., 3., 4., and 5.). When examining the ANFIS models created with 75% training and 25% testing data, the 4 models that provide the best estimate are listed in Table 2. The performances of each model clearly show that they are at an acceptable level when the statistical parameters are examined. The ANFIS model (3 2 2), which gives the best estimation results, is the model with a network structure. The values of

RMSE, R^2, RSE and MAE calculated with this model are 8.3314; 0.9616; 3.1639; 0.0371 and 6.6190; 0.9896; 1.4275; 0.0315 for training and test, respectively.

Table 2. RMSE, R^2, RSE, and MAE values show the success of each network with different models in estimating 75% training and 25% test data.

ANFIS Models	RMSE	R^2	RSE	MAE	SD	SC	KC
				ANFIS Results (75% Train)			
2 2 2	8.8881	0.9563	3.4007	0.0401	42.3763	0.6657	-0.5085
3 2 2	8.3314	0.9616	3.1639	0.0371	42.4936	0.5186	-0.7754
3 3 2	6.1061	0.9794	2.2194	0.0217	42.8843	0.5305	-0.7862
4 2 3	5.0550	0.9859	2.0809	0.0222	43.0171	0.6052	-0.5063
				ANFIS Results (25% Test)			
ANFIS Models	**RMSE**	**R^2**	**RSE**	**MAE**	**SD**	**SC**	**KC**
2 2 2	9.7120	0.9678	2.1230	0.0493	57.3941	0.3023	-1.7674
3 2 2	**6.6190**	**0.9896**	**1.4275**	**0.0315**	**53.7700**	**0.1450**	**-1.8373**
3 3 2	9.4916	0.9778	1.9716	0.0373	61.0551	0.1048	-1.6977
4 2 3	9.4032	0.9771	2.1431	0.0473	59.1558	0.2923	-1.7883

Examining the ANFIS models created with 77% training and 23% test data, the 4 models that provide the best estimate are shown in Table 3. The performances of each model clearly show that they are at an acceptable level when the statistical parameters are examined. The ANFIS model (3 2 2), which gives the best estimation results, is the model with a network structure. The values of RMSE, R^2, RSE and MAE calculated with this model are 8.1909; 0.9645; 3.1706; 0.0368 and 6.8254; 0.9887; 1.3474; 0.0277 for training and test, respectively.

Table 3. RMSE, R^2, RSE, and MAE values show the success of each network with different models in estimating 77% training and 23% test data.

ANFIS Models	RMSE	R^2	RSE	MAE	SD	SC	KC
				ANFIS Results (77% Train)			
2 2 2	8.7895	0.9591	3.4344	0.0403	43.3497	0.6444	-0.5287
3 2 2	8.1909	0.9645	3.1706	0.0368	43.4740	0.5030	-0.7742
3 3 2	6.0086	0.9809	2.2306	0.0215	43.8392	0.5153	-0.7767
4 2 3	5.0449	0.9865	2.1318	0.0240	43.9564	0.5860	-0.5206
				ANFIS Results (23% Test)			
ANFIS Models	**RMSE**	**R^2**	**RSE**	**MAE**	**SD**	**SC**	**KC**
2 2 2	9.9423	0.9677	1.9664	0.0449	56.9698	0.1491	-1.8554
3 2 2	**6.8254**	**0.9887**	**1.3474**	**0.0277**	**52.2985**	**-0.0150**	**-1.8448**
3 3 2	9.7437	0.9718	1.8411	0.0338	56.4979	0.0370	-1.7253
4 2 3	8.6913	0.9845	1.6491	0.0308	59.4890	0.1030	-1.8416

Examining the ANFIS models created with 80% training and 20% test data, the 8 models that provide the best estimate are shown in Table 4. The performances of each model clearly show that they are at an acceptable level when the statistical parameters are examined. The ANFIS model (4 2 2), which provides the best estimation results, is the model with a network structure. The values of RMSE, R^2, RSE, and MAE calculated with this model are 6.1888; 0.9807; 2.5697; 0.0312 and 4.5227; 0.9948; 0.9222; 0.0221 for training and test, respectively.

Table 4. RMSE, R^2, RSE, and MAE values show the success of each network with different models in estimating 80% training and 20% test data.

ANFIS Models	RMSE	R^2	RSE	MAE	SD	SC	KC
			ANFIS Results (80% Train)				
2 2 2	8.6386	0.9625	3.4300	0.0362	44.5268	0.5136	-0.8554
3 2 2	8.0817	0.9672	3.1818	0.0364	44.6349	0.4229	-0.9747
3 3 2	6.0139	0.9818	2.2697	0.0223	44.9717	0.4307	-0.9835
4 2 2	6.1888	0.9807	2.5697	0.0312	44.9373	0.4743	-0.8204
4 2 3	4.9571	0.9876	2.1318	0.0232	45.0970	0.4989	-0.7593
5 2 2	4.9154	0.9879	2.0164	0.0225	45.1015	0.4702	-0.8310
6 2 2	4.8326	0.9883	1.9683	0.0218	45.1139	0.4655	-0.8264
7 2 2	4.8535	0.9882	1.9718	0.0218	45.1125	0.4625	-0.8221
			ANFIS Results (20% Test)				
ANFIS Models	**RMSE**	**R^2**	**RSE**	**MAE**	**SD**	**SC**	**KC**
2 2 2	6.7000	0.9872	1.2671	0.0326	52.7138	0.3129	-1.6956
3 2 2	6.5533	0.9865	1.2292	0.0279	52.3592	0.2231	-1.7442
3 3 2	9.5516	0.9876	1.6957	0.0319	58.4175	0.2461	-1.7112
4 2 2	**4.5227**	**0.9948**	**0.9222**	**0.0221**	**55.6920**	**0.2582**	**-1.7743**
4 2 3	9.3618	0.9890	1.6604	0.0344	60.5537	0.3394	-1.7352
5 2 2	9.9352	0.9778	2.0016	0.0403	53.8338	0.0362	-1.7688
6 2 2	6.9199	0.9928	1.4191	0.0352	52.8038	0.1011	-1.6957
7 2 2	6.6184	0.9938	1.3975	0.0352	52.2768	0.1278	-1.6621

Examining the ANFIS models created with 83% training data and 17% test data, the 10 models that provide the best estimate are shown in Table 5. The performances of each model clearly show that they are at an acceptable level when the statistical parameters are examined. The ANFIS model (4 2 2), which provides the best estimation results, is the model with a network structure. The values of RMSE, R^2, RSE and MAE calculated with this model are 6.1169; 0.9805; 2.5854; 0.0310 and 4.6646; 0.9952; 0.8792; 0.0224 for training and test, respectively.

Table 5. RMSE, R^2, RSE, and MAE values show the success of each network with different models in estimating 83% training and 17% test data.

ANFIS Models	RMSE	R^2	RSE	MAE	SD	SC	KC
			ANFIS Results (83% Train)				
2 2 2	8.6148	0.9614	3.4914	0.0367	43.7310	0.5338	-0.7670
2 2 3	5.7197	0.9830	2.2914	0.0222	44.2192	0.5303	-0.7251
3 2 2	7.9708	0.9670	3.1946	0.0361	43.8571	0.4529	-0.9043
3 2 3	4.6487	0.9880	1.8058	0.0144	44.3488	0.4575	-0.8328
3 3 2	6.0508	0.9810	2.3330	0.0228	44.1735	0.4281	-0.9114
4 2 2	6.1169	0.9805	2.5854	0.0310	44.1543	0.4783	-0.7447
4 2 3	4.9262	0.9874	2.1557	0.0233	44.3099	0.5020	-0.6804
5 2 2	4.8802	0.9876	2.0371	0.0233	44.3153	0.4716	-0.7556
6 2 2	4.7925	0.9881	1.9859	0.0215	44.3281	0.4668	-0.7504
7 2 2	4.8026	0.9880	1.9835	0.0214	44.3279	0.4638	-0.7461
			ANFIS Results (17% Test)				
ANFIS Models	**RMSE**	**R^2**	**RSE**	**MAE**	**SD**	**SC**	**KC**
2 2 2	6.3354	0.9884	1.0828	0.0296	57.6547	0.2313	-1.9559
2 2 3	9.4975	0.9953	1.5313	0.0313	64.8968	0.2571	-1.9926
3 2 2	6.9270	0.9862	1.1969	0.0292	57.3332	0.1763	-1.9886
3 2 3	9.7903	0.9939	1.6309	0.0386	63.4368	0.1787	-1.9983
3 3 2	9.6031	0.9880	1.5418	0.0282	64.1100	0.2356	-1.9502
4 2 2	**4.6646**	**0.9952**	**0.8792**	**0.0224**	**60.9472**	**0.1930**	**-2.0165**
4 2 3	9.9369	0.9916	1.6225	0.0357	66.1738	0.2448	-1.9915
5 2 2	9.9943	0.9796	1.8362	0.0375	59.4356	0.0168	-2.0201
6 2 2	6.8553	0.9932	1.2772	0.0332	58.2827	0.0704	-1.9607
7 2 2	6.5501	0.9945	1.2655	0.0343	57.6082	0.0895	-1.9302

When the statistical parameters were examined, it was found that the data used 80% for training and 20% for testing gave the best results in estimating the shear strength of the ANFIS model (4 2 2). The architecture of the ANFIS model that provided the best estimates is shown in Figure 3.

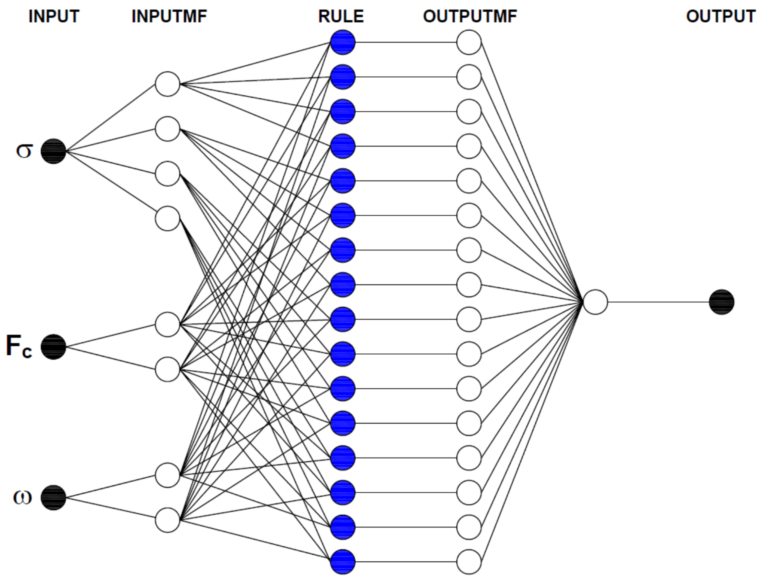

Figure 3. Structure of the ANFIS model, which provides the best predictions

The regression graphs showing the relationship between the output values of the network with the best performance and the measured values are presented in Figure 4.

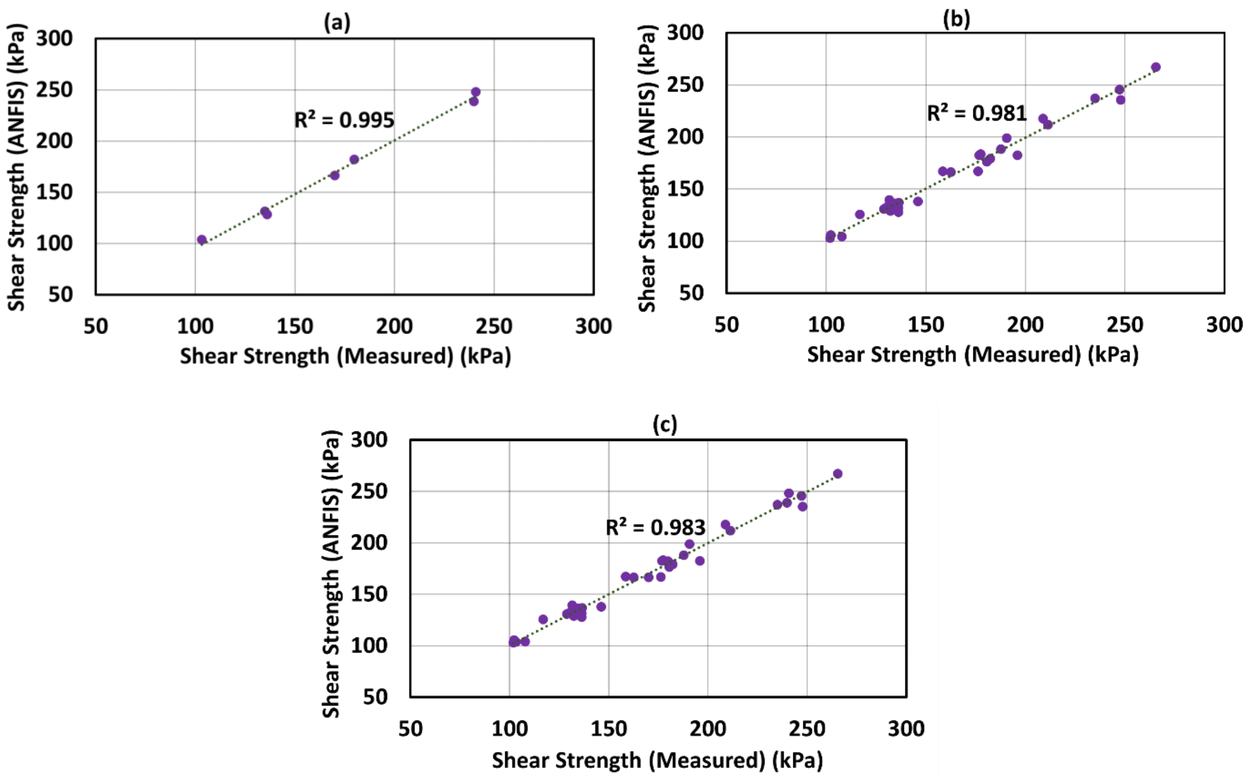

Figure 4. Regression plots for the best ANFIS-based prediction model, (a) training data, (b) testing data, and (c) all data

To better understand the performance of the ANFIS, the predictions of the network and the corresponding measured values were compared in both the training and test phases (Figure 5).

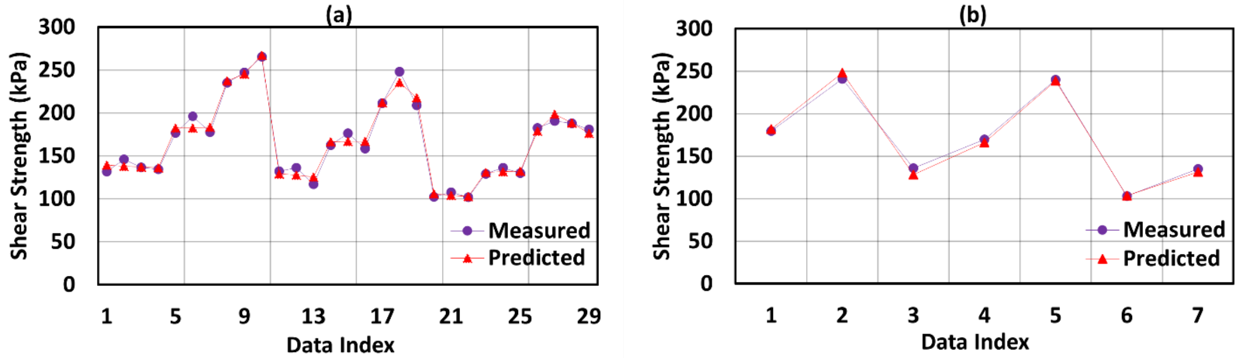

Figure 5. Comparison of predicted and measured shear strength values; (a) training data, (b) test data

In general, when studying the shear strength of glass fiber reinforced clay soils with ANFIS models, it was found that the shear strength estimates agree very well with the tests performed in the laboratory. This situation clearly shows us that the ANFIS artificial intelligence algorithm can be used to find fast and economical solutions for shear strength tests, which are complicated, expensive, and time-consuming depending on the type of experiment.

4. Conclusions

In this study, an ANFIS model was developed using fiber content, water content, and normal stress applied in the direct shear test as input parameters to predict the shear strength of glass fiber reinforced clay soil. To determine the best fit ANFIS model in the current study, 75%, 77%, 80%, and 83% of the data were used for training and 25%, 23%, 20%, and 17% for testing, respectively. The indicators RMSE, R^2, RSE, and MAE were used to evaluate the performance of the network. The study of the statistical parameters showed that the data used 80% for training and 20% for testing gave the best results in estimating the shear strength of the ANFIS model. Therefore, the ANFIS method can be used as an excellent artificial intelligence algorithm to estimate the shear strength of glass fiber reinforced clay soil.

In future studies, the scope of the shear strength calculation can be expanded by adding new input parameters. Using the estimated data obtained from ANFIS models, experimental comparisons can be made in the laboratory. In addition, the amount of data can be increased when ANFIS models are created. It is believed that more successful results can be obtained in estimating shear strength using ANFIS models if the number of data is increased.

Authors' contributions

All authors contributed equally to the writing of this article.

Competing interests

The authors declare that they have no competing interests.

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