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Prediction of Shear Strength Parameters of Gypseous Soil using Artificial Neural Networks

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ABSTRACT

The shear strength of soil is one of the most important soil properties that should be identified before any foundation design. The presence of gypseous soil exacerbates foundation problems. In this research, an approach to forecasting shear strength parameters of gypseous soils based on basic soil properties was created using Artificial Neural Networks. Two models were built to forecast the cohesion and the angle of internal friction. Nine basic soil properties were used as inputs to both models for they were considered to have the most significant impact on soil shear strength, namely: depth, gypsum content, passing sieve no.200, liquid limit, plastic limit, plasticity index, water content, dry unit weight, and initial voids ratio. Multi-layer perceptron training by the backpropagation algorithm was used in creating the network. It was found that both models can predict shear strength parameters for gypseous soils with good reliability. Sensitivity analysis of the first model indicated that dry unit weight and plasticity index have the most significant effect on the predicted cohesion. While in the second model, the results indicated that the gypsum content and plasticity index have the most significant effect on the predicted angle of internal friction.
Keywords: Gypseous soil, Cohesion, Angle of internal friction, Artificial Neural Networks.

التنبؤ بمعاملات مقاومة القص للترب الجبسية باستخدام الشبكات العصبية الاصطناعية

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الخلاصة

تعد مقاومة القص من أهم خصائص التربة التي يتوجب تحديدها قبل تصميم أي أساس. وتتفاقم مشاكل الأسس بسبب وجود التربة الجبسية. تم في هذا البحث، ايجاد طريقة للتنبؤ بمعاملات مقاومة القص للترب الجبسية بناءً على الخصائص الأساسية

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للتربة باستخدام الشبكات العصبية الاصطناعية. فقد تم بناء نموذجين للتنبؤ بالتماسك وزاوية الاحتكاك الداخلي. إذ تم استخدام تسعة خصائص أساسية للتربة كمدخلات لكلا النموذجين لأنها تعد ذات التأثير الأكثر أهمية على مقاومة قص التربة، وهي: العمق، محتوى الجبس، نسبة المار من غربال رقم 200، حد السيولة، حد اللدونة، مؤشر اللدونة، محتوى الماء، وحدة الوزن الجاف، ونسبة الفراغات الأولية. وتم تدريب الشبكة بطريقة المستقبلات متعددة الطبقات باستخدام خوارزمية الانتشار العكسي لأجل بناء النموذج. وقد وجد أن لكلا النموذجين القدرة على التنبؤ بمعاملات مقاومة القص للترب الجبسية بموثوقية جيدة. حيث أشار تحليل الحساسية للنموذج الأول إلى أن وحدة الوزن الجاف ومؤشر اللدونة لهما التأثير الأكبر على القيمة المتوقعة للتماسك. بينما أشارت النتائج في النموذج الثاني إلى أن محتوى الجبس ومؤشر اللدونة لهما التأثير الأكبر على القيمة المتوقعة لزاوية الاحتكاك الداخلي.

الكلمات الرئيسية: التربة الجبسية، التماسك، زاوية الاحتكاك الداخلي، الشبكات العصبية الاصطناعية.

1. INTRODUCTION

Gypseous soils are one of the most problematic materials that challenge geotechnical engineers. Constructions on gypseous soil may experience unpredictable deformations, which may cause catastrophic failure. Several structures in Iraq have encountered various patterns of cracks and settlements primarily generated from the dissolution of bonding materials of soil particles due to water-table fluctuation. Gypseous soils demonstrate high bearing capacity and very low compressibility when dry. On the contrary, sudden collapsible behavior is expected when they are exposed to water (**Al-Saoudi et al., 2013**).

Gypseous soils are widely distributed, especially in Iraq, where the arid area of hot climatic is present **(Shakir, 2017).**

Using standard experimental tests, determining soil geotechnical parameters is often costly and time-consuming, especially when investigating wide areas. It becomes more complicated when dealing with gypseous soil. A technically acceptable alternative approach is required to predict those parameters based on easily determined soil properties. The Artificial Neural Networks (ANN) technique has already been used as a prediction method to deal with some geotechnical aspects; therefore, it can be examined to fit the prediction of shear strength parameters (C) and (φ) too.

Concerning previous studies on shear strength parameters, some recent related studies can be summarized as follows:

(Al-Ameery, 2003) used gypseous soil from Al-Daur town with (66.4%) gypsum content. The results of the Triaxil test of saturated gypseous soil showed a (38%) reduction in cohesion (C) and (52%) reduction in the angle of internal friction (φ) due to soaking.

(Khan, 2005) used gypseous soil with (37%) and (57%) gypsum content, where it was found that both cohesion and the angle of internal friction increased with increased compaction effort. The cohesion continued to grow with increased molding water under various compaction efforts until it had reached its maximum water content and then began to decrease in the same manner as a compaction curve did. However, the angle of internal friction decreased with increased molding water content.

(Karim et al., 2013) used gypseous soil from Al-Qarma town with a gypsum content of (50%). The direct shear test showed that shear strength parameters increased and then decreased with increased kaolinite and bentonite additives. Higher shear strength parameters were obtained when bentonite was used rather than kaolinite for the same percentages of additives. It was concluded that bentonite was much more effective in increasing (C) and reducing (φ) than kaolinite. However, kaolinite was much more effective in reducing (C) than bentonite.

(Khaboushan et al., 2018) predicted unsaturated shear strength parameters for soils with different clay, sand, and silt percentages, particle size, organic matter (OM) content, and calcium carbonate ($CaCO_3$) content. Fourteen soil samples from Northeast Iran were used, and Multiple Linear Regression (MLR) was utilized to estimate the shear strength parameters of saturated soil tested by direct shear tests.
(Schanz and Karim, 2018) studied the effect of the short-term soaking period on shear strength parameters (C and φ) of (12) gypseous soil samples from Tikrit town. Direct shear tests using a pneumatic shear device were carried out on (4) dry and (8) soaked soil samples, in which (4) were soaked in water for (6 hr) and (4) were soaked for (24 hr). The normal stresses used were (50, 100, 200, and 400 kPa). The results for the (6 hr) soaked samples showed a (12.24%) reduction in the angle of internal friction and (91.5%) reduction in cohesion compared to dry samples. However, the results for the (24 hr) soaked samples showed (9.2%) reduction in the angle of internal friction and (94.24%) reduction in cohesion compared to dry samples. The loss in strength due to soaking was clearly noticed in cohesion, which can be attributed to softening.
(Najemalden et al., 2020) used a backpropagation neural network approach to model the relation between the collapse potential of gypseous sandy soil and seven soil properties employed as inputs, including gypsum content, specific gravity, initial dry unit weight, initial degree of saturation, initial voids ratio, initial water content and passing sieve #200. The relative importance analysis revealed that the specific gravity and gypsum content were the most important factors. The results revealed the veracity of using ANNs as an effective method to estimate the collapse potential of gypseous sandy soils.
(Mawlood, 2021) used linear and nonlinear regression to simulate shear strength parameters and compressibility characteristics of gypseous soils. A set of 220 data items gathered from several published articles were used. The compression index and collapse potential were found to be well predicted in terms of gypsum concentration, initial water content, initial voids ratio, liquid limit, plasticity index, total unit weight, and dry unit weight using adjusted (R^2), Mean Absolute Error, and Root Mean Square Error. The sensitivity analysis of the models revealed that the liquid limit and total unit weight were the most influential parameters in determining cohesion and angle of internal friction, while the ratio of specific gravity to initial voids ratio was the most significant physical soil property in estimating the collapse potential.
(Mohammed et al., 2021) also used linear and nonlinear regression to estimate shear strength parameters, collapse potential, and compression index of gypseous soils based on physical properties by utilizing a set of 220 data items from several published studies. It was found that the developed models did accurately predict the outputs as a function of the available inputs, including specific gravity, moisture content, density, and Atterberg limits. It was also found that the gypsum content was well associated with total soluble salts, sulfate, and pH values. The models were tested using the adjusted (R^2), Mean Absolute Error, and Root Mean Square Error.
Other researchers have also conducted studies to forecast shear strength parameters (C and φ) using different methods, e.g. **(Mahmoud, 2013)** used standard penetration test and **(Abu-Farsakh and Titi in 2004)** used cone penetration test.
This research aims to develop two reliable mathematical models capable of predicting shear strength parameters of gypseous soils; cohesion (C) and angle of internal friction (φ) based on basic soil properties using the ANN technique. Nine input parameters were used, aiming at more precise results.

2. RESEARCH METHODOLOGY

The research paradigm correlates relevant geotechnical data using the Artificial Neural Networks technique to develop mathematical prediction models subjected to statistical analysis.
The following steps were carried out:

- Factual data available at different sources were collected concerning cohesion (C) and internal angle of friction (φ) of gypseous soils in different territories in Iraq.
- Relevant soil properties needed to build suitable prediction models were identified.
- The ANNs technique basics, characteristics, elements, and types, especially perceptrons, layers, and algorithms, were carefully studied and employed for modeling.
- Models Creation using the ANNs technique.
- Statistical analyses were carried out to test the reliability of the results.

2.1 Research Limitation

The effect of applied stress and degree of saturation on cohesion (C) and internal angle of friction (φ) were not taken into consideration due to the scarcity of relevant data of gypseous soils in different territories in Iraq.

3. ARTIFICIAL NEURAL NETWORK

Artificial Neural Network consists of a large number of units known as nodes. Weighted links connect each node to the other nodes. These weights represent information used by the net to solve the case to be solved. This network is composed of many layers of nodes. The first layer is the input layer, where the inputs (dependent variables) are applied to the net. The last layer is the output layer, where the outputs (independent) are extracted. A number of nodes serve as preceding items in the hidden layers between the input and output **(Al-Musawi, 2016).** The true power and advantage of ANN lie in its ability to represent both linear and nonlinear relationships from data being modeled **(Lal and Tripathy, 2012)**.
The input from each processing element in the previous layer (x_i) is multiplied by an adjustable connection weight (w_{ij}) at each processing element, the weighted input signals are summed, and a threshold value (θ_j) may be added. This combined input (I_j) is then passed through a transfer (activation) function $f(I_j)$ to produce the output of the processing element (y_j). The output of one processing element provides the input to the processing elements in the next layer. This process is summarized in equations (1) and (2) **(Al-Janabi, 2006)**.

$$I_j = \sum w_{ji} x_i + \theta_j \tag{1}$$

$$y_j = f(I_j) \tag{2}$$

where:
I_j: is the activation level of node (j),
w_{ji}: is the connection weight between (j) and (i),
x_i: is the input from node (i) for (i = 0, 1… n),
θ_j: is the bias or threshold for node (j),
y_j: is the output of node (j), and
$f(I_j)$: is the transfer (activation) function.

The best sets of random data divisions were used to develop each model, which was found to be (33) data for training, (7) data for testing, and (10) data for validation for model (C). On the other hand, the best sets were (30) data for training, (6) data for testing, and (14) data for validation for model (φ). Default parameters of the SPSS v.23 programs were utilized to select a learning rate of

(0.4), momentum term of (0.9), and tanh or sig transfer functions in the hidden and output layers nodes. Several networks with different number of hidden nodes were tried. A network with two hidden nodes was found to be the best for model (C) using tanh transfer function in the hidden and output layers nodes. The testing set of this model revealed the lowest prediction error of (0.016%) with a high coefficient of correlation (R = 97.63%) and a high coefficient of determination (R^2 = 95.33%). On the other hand, a network with two hidden nodes was found to be the best for model (φ) using the sig transfer function in the hidden layer nodes and the tanh transfer function in the output layer nodes. The testing set of this model revealed the lowest prediction error of (0.283%) with the coefficient of correlation (R = 99.31%) and a high coefficient of determination (R^2 = 98.63%).

The effects of using different transfer functions were also investigated for both models. For model (C), a better performance was obtained when the (tanh vs. tanh) transfer function was used for both hidden and output layers, as shown in **Table 1**. For model (φ), the better performance was obtained when the (sigmod vs. tanh) transfer function was used for both hidden and output layers, as shown in **Table 2**.

Table 1. Effect of transfer functions on the performance of the model (C).

Parameters	Transfer Function		Training SSE*	Testing SSE*	Validation SSE*	R	R²
	Hidden layer	Output layer					
Model (C)	Tanh	tanh	0.038	0.016	0.410	97.6%	95.33%
Learning rate (0.4)	tanh	sigmod	0.030	0.048	0.101	96.6%	93.90%
Momentum rate (0.9)	sigmod	sigmod	0.085	0.071	0.902	90.5%	82.0%
No. of Nodes (2)	sigmod	tanh	0.040	0.040	0.252	89.5%	80.0%

* Sum of Squared Error.

Table 2. Effect of transfer functions on the performance of the model (φ).

Parameters	Transfer Function		Training SSE*	Testing SSE*	Validation SSE*	R	R²
	Hidden layer	Output layer					
Model (φ)	Tanh	tanh	0.085	0.455	0.161	98.1%	96.2%
Learning rate (0.4)	tanh	sigmod	0.026	0.284	0.046	98.0%	96.00%
Momentum rate (0.9)	sigmod	sigmod	0.884	0.891	0.972	96.0%	92.1%
No. of Nodes (2)	sigmod	tanh	0.014	0.283	0.015	99.31%	98.63%

* Sum of Squared Error.

4. INPUT AND OUTPUT VARIABLES

A compilation of available data on gypseous soils from different regions in Iraq was derived from fifty research publications, theses, and dissertations showing laboratory tests results of gypseous soil shear strength parameters (C) and (φ). Nine parameters were used as inputs to develop two prediction models using SPSS V23. Two mathematical equations to predict cohesion (C) and angle of internal friction (φ) were determined. The input parameters included: depth, gypsum content, liquid limit (LL), plastic limit (PL), plasticity index (PI), passing sieve #200, dry unit weight (γ_d), water content (wc), and initial void ratio (e_o).

Statistical analysis was carried out to ensure that the subsets of training, testing, and validation data represent the same statistical population as shown in **Tables 3** and **4**. The results indicated that these subsets were statistically consistent. Furthermore, t-tests were also carried out to examine how these subsets are statistically consistent with respect to each other. The tests were based on a level of confidence of (95%). The results of t-tests are given in **Tables 5** and **6**.

Table 3. Input and output statistics for cohesion (C) ANN model.

Data set	Statistical Parameters	Actual Input Variables									Actual Output
		Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e_o	C (kPa)
Training n = 33	Range	14.200	65.940	62.000	32.000	44.000	92.000	11.510	29.900	0.695	74.205
	Min.	0.800	4.060	18.000	8.000	5.000	8.000	11.700	3.600	0.200	10.125
	Max.	15.000	70.000	80.000	40.000	49.000	100.000	23.210	33.500	0.895	84.330
	Mean	2.733	28.368	45.514	24.653	23.315	69.917	16.440	15.564	0.588	24.584
	Std.	3.573	20.053	14.414	9.446	10.928	32.781	2.620	7.747	0.194	15.581
Testing n = 7	Range	3.500	40.580	34.700	7.240	28.800	6.700	3.000	7.980	0.265	33.809
	Min.	1.500	2.600	21.000	18.260	1.400	93.300	14.800	12.520	0.435	10.747
	Max.	5.000	43.180	55.700	25.500	30.200	100.000	17.800	20.500	0.700	44.555
	Mean	2.786	14.754	41.814	20.680	21.134	98.086	16.540	17.060	0.574	21.903
	Std.	1.286	13.848	10.958	2.428	9.984	3.269	1.178	2.666	0.128	11.444
Validation n = 10	Range	1.000	55.490	28.500	19.000	25.800	91.000	6.500	19.300	0.605	25.904
	Min.	Depth	5.010	26.500	20.000	5.200	8.000	12.600	6.500	0.310	10.329
	Max.	14.200	60.500	55.000	39.000	31.000	99.000	19.100	25.800	0.915	36.233
	Mean	0.800	29.061	41.350	25.230	16.120	58.150	15.578	14.310	0.666	24.977
	Std.	15.000	17.182	8.648	6.121	7.990	38.140	1.754	4.942	0.169	7.496

Table 4. Input and output statistics for the angle of internal friction (φ) ANN model.

Data set	Statistical Parameters	Actual Input Variables									Actual Output
		Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e_o	C (kPa)
Training n = 30	Range	14.200	65.940	62.000	32.000	44.000	92.000	11.510	29.900	0.695	12.368
	Min.	0.800	4.060	18.000	8.000	5.000	8.000	11.700	3.600	0.200	23.997
	Max.	15.000	70.000	80.000	40.000	49.000	100.000	23.210	33.500	0.895	36.365
	Mean	2.880	29.698	45.732	25.118	23.313	66.909	16.326	15.529	0.594	30.168
	Std.	3.717	20.453	15.100	9.788	11.472	32.905	2.717	8.125	0.200	3.181
Testing n = 6	Range	4.200	15.220	7.000	3.000	7.000	0.000	1.410	3.250	0.217	1.122
	Min.	0.800	5.000	40.000	19.000	18.000	100.000	16.690	14.500	0.423	29.377
	Max.	5.000	20.220	47.000	22.000	25.000	100.000	18.100	17.750	0.640	30.498
	Mean	2.633	15.037	41.667	20.167	21.500	100.000	17.612	16.042	0.483	29.942
	Std.	1.675	6.360	2.733	1.472	2.429	0.000	0.500	1.066	0.084	0.392
Validation n = 14	Range	1.000	57.900	34.700	20.740	29.600	92.000	6.500	19.300	0.605	6.736
	Min.	1.000	2.600	21.000	18.260	1.400	8.000	12.600	6.500	0.310	27.864
	Max.	2.000	60.500	55.700	39.000	31.000	100.000	19.100	25.800	0.915	34.600
	Mean	1.607	24.921	41.871	24.004	17.867	69.150	15.616	15.287	0.668	30.617
	Std.	0.446	18.308	10.324	5.683	9.858	36.555	1.509	4.736	0.142	2.160

4.1 Data Division (Preparation)

The ANNs used were Multi-Layer Perceptrons trained with the feed-forward backpropagation algorithm. The typical MLP has a number of processing elements generally known as neurons which are arranged in layers, including an input layer, an output layer, and one hidden layer. Each neuron in the specific layer is connected to the neuron of other layers through a weighted connection. The input from each neuron in the previous layer is multiplied by an adjustable connection weight.

The available data were divided into subsets to develop the ANN model. Subsets were checked using the SPSS v.23 program to ensure the best data division. The default parameters of the SPSS program which were applied were: linear activation function for input layer and tanh function for both hidden and output layers.

Table 5. Results of cohesion (C) ANN model t-test.

Statistical	Input Variables	Actual

Parameters										Output
	Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e°	C (kPa)
Data set	Testing									
t-value	-0.0379	1.7034	0.6384	2.1098	0.4860	-2.2482	-0.0978	-0.8885	0.1924	0.4295
Lower critical value	-2.8478	-2.5654	-8.0318	0.1549	-6.9039	-53.5332	-2.1628	-4.9377	-0.1408	-9.9572
Upper critical value	2.7430	29.7938	15.4305	7.7911	11.2656	-2.8043	1.9634	1.9462	0.1704	15.3208
Sig.(2-tailed)	0.9699	0.0967	0.5271	0.0418	0.6298	0.0504	0.9226	0.3815	0.8484	0.6700
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
Data set	Validation									
t-value	1.0798	-0.0986	1.1219	-0.2272	1.9250	0.9579	0.9727	0.4809	-1.1379	-0.0766
Lower critical value	-1.0734	-14.8781	-3.4731	-5.8275	-0.3534	-13.0407	-0.9280	-4.0130	-0.2149	-10.7489
Upper critical value	3.5401	13.4930	11.8004	4.6735	14.7437	36.5747	2.6526	6.5215	0.0600	9.9631
Sig.(2-tailed)	0.2866	0.9219	0.2724	0.8223	0.0612	0.3437	0.3364	0.6331	0.2618	0.9393
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept

Table 6. Results of the angle of internal friction (φ) ANN model t-test.

Statistical Parameters	Input Variables									Actual Output
	Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e°	C (kPa)
Data set	Testing									
t-value	0.1579	3.2236	1.3668	2.6265	0.7825	-5.5082	-1.1420	-0.3316	1.3269	0.3740
Lower critical value	-2.9271	5.3307	-1.9791	1.1180	-2.8980	-45.3784	-3.5727	-3.6588	-0.0592	-1.0009
Upper critical value	3.4205	23.9919	10.1091	8.7854	6.5247	-20.8043	1.0020	2.6335	0.2821	1.4515
Sig.(2-tailed)	0.8754	0.4033	0.1807	0.0629	0.4394	0.0559	0.2614	0.7423	0.1934	0.7108
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept
Data set	Validation									
t-value	1.8475	0.7449	0.8643	0.4750	1.5299	-0.2032	0.9105	0.1240	-1.2418	-0.4781
Lower critical value	-0.1328	-8.1651	-5.1536	-3.6266	-1.7376	-24.5001	-0.8636	-3.7004	-0.1943	-2.3458
Upper critical value	2.6785	17.7197	12.8741	5.8547	12.6300	20.0174	2.2834	4.1841	0.0463	1.4471
Sig.(2-tailed)	0.0743	0.4605	0.3924	0.6374	0.1335	0.8400	0.3678	0.9019	0.2212	0.6350
Results	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept	Accept

Based on the minimum error of the testing set, the coefficient of correlation (R), and coefficient of determination (R^2), the best data division into subsets was found to be as shown in **Table 7**. Output and input variables were pre-processed by scaling them to repeal their dimension in order to assure that all variables receive equal attention during training and to be proportional to the limits of the transfer functions used in hidden and output layers (0.0) to (1.0) for sigmoid transfer function and (-1.0) to (1.0) for tanh transfer function. The scaled value (x_n) is found by equation (3) **(Mahmood and Aziz, 2011)**:

$$Scale\ value = \frac{X - Xmin}{Xmax - Xmin} \tag{3}$$

where:
x: is the original value,
x_{min} and x_{max}: are the actual minimum and maximum values.

Table 7. Best data division into subsets.

Model (C) for Cohesion					Model (φ) for Angle of Friction				
Number and (%)			R	R^2	Number and (%)			R	R^2
Training	Validation	Testing			Training	Validation	Testing		
33 (66%)	10 (20%)	7 (14%)	97.63%	95.33%	30 (60%)	14 (28%)	6 (12%)	99.31%	98.63%

4.2 Evaluation Criteria

The statistical methods used to measure models output included:

- Mean Percentage Error (MPE).
- Root Mean Squared Error (RMSE).
- Mean Absolute Percentage Error (MAPE).
- Average Accuracy Percentage (AA%).
- The Coefficient of Determination (R^2).
- The Coefficient of Correlation (R).

5. OPTIMUM ANN MODELS

The connection weights obtained for both optimal ANN models (cohesion and angle of internal friction) enables each network to be translated into a relatively simple formula. **Tables 8** and **9** list each model's connection weights and threshold levels.

Table 8. Parameter Estimates for the cohesion optimal ANN model (C).

Layer	Predictor	Input Layer										Hidden Layer 1		
		(Bias)	Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e_o	(Bias)	H(1:1)	H(1:2)
Predicted														
Hidden Layer1	H(1:1)	.104	.387	-.129	.337	-.433	-.059	.217	-.719	-.106	-.003			
	H(1:2)	.024	0.033	-.080	.498	.274	.931	.524	-1.456	-.480	.007			
Output Layer	C											0.302	0.629	2.118

Table 9. Parameter Estimates for the angle of internal friction optimal ANN model (φ).

Layer	Predictor	Input Layer										Hidden Layer 1		
		(Bias)	Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e_o	(Bias)	H(1:1)	H(1:2)
Predicted														
Hidden Layer1	H(1:1)	-.917	1.185	-1.074	.305	.601	1.154	-.389	.589	-.366	.608			
	H(1:2)	.014	-.440	.586	.350	-.283	-.292	-.226	-.858	.236	-.428			
Output Layer	C											.811	-2.808	1.403

The predicted cohesion (C kPa) was found to be expressed as follows:

$$(C)_{nor} = Tanh\ [0.302 + 0.629 * H_1 + 2.118 * H_2] \tag{4}$$

$$H_1 = \left[\frac{1}{1+e^{(-X_1)}}\right] \tag{5}$$

$$H_2 = \left[\frac{1}{1+e^{(-X_2)}}\right] \tag{6}$$

$$x_1 = \{0.104 + (0.387 * depth) - (0.129 * gypsum) + (0.337 * L.L) - (0.433 * P.L) - (0.059 * P.I) + (0.217 * Sieve) - (0.719 * \gamma d) - (0.106 * wc) - (0.003 * eo)\} \tag{7}$$

$$x_2 = \{0.024 - (0.033 * depth) - (0.080 * gypsum) + (0.498 * L.L) + (0.274 * P.L) + (0.931 * P.I) + (0.524 * Sieve) - (1.456 * \gamma d) - (0.480 * wc) + (0.007 * eo)\} \tag{8}$$

$$(C)_{act} = [(C)nor * range + min] \tag{9}$$

$$(C)_{act} = [(C)nor * 74.205 + 10.125] \tag{10}$$

where:
$(C)_{act}$: is the actual cohesion,
H_1, H_2: are the connection weights,
x_1, x_2: are outputs, and
$(C)_{nor}$: is the normalized cohesion.

The predicted angle of internal friction (φ) was found to be expressed as follows:

$$(\varphi)_{nor} = Tanh\,[0.811 - 2.808 * H_1 + 1.403 * H_2] \tag{11}$$

$$H_1 = \left[\frac{1}{1+e^{(-X_1)}}\right] \tag{12}$$

$$H_2 = \left[\frac{1}{1+e^{(-X_2)}}\right] \tag{13}$$

$$x_1 = \{-0.917 + (1.187 * depth) - (1.074 * gypsum) + (0.305 * L.L) + (0.601 * P.L) + (1.154 * P.I) - (0.389 * Sieve) + (0.589 * \gamma d) - (0.366 * wc) + (0.608 * eo)\} \tag{14}$$

$$x_2 = \{0.014 - (0.440 * depth) + (0.856 * gypsum) + (0.350 * L.L) - (0.283 * P.L) - (0.292 * P.I) - (0.226 * Sieve) - (0.858 * \gamma d) + (0.236 * wc) - (0.428 * eo)\} \tag{15}$$

$$(\varphi)_{act} = [(\varphi)nor * range + min] \tag{16}$$

$$(\varphi)_{act} = [(\varphi)nor * 13.368 + 23.997] \tag{17}$$

where:
$(\varphi)_{act}$: is the actual angle of internal friction,
H_1, H_2: are the connection weights,
x_1, x_2: are outputs, and
$(\varphi)_{nor}$: is the normalized angle of internal friction.

5.1 Model Performance Evaluation

According to **(Khaled, et al., 2014)**, the statistical measures shown in **Tables 10** and **11** were used to measure the shear strength parameters of both prediction models. Results related to models (C) and (φ) are also shown in both tables.

Table 10. Performance measures for the cohesion Model (C).

MPE	RMSE	MAPE	AA%	R	R^2
1.650%	2.000	7.374%	92.626%	97.63%	95.33%

Table 11. Performance measures for the angle of internal friction Model (φ).

MPE	RMSE	MAPE	AA%	R	R^2
-0.1521%	0.253	0.679%	99.321%	99.31%	98.63%

To explore the validity of the derived equations for both ANN models, predicted values of (C) and (φ) were drawn against actual (observed validation data) values as shown in **Fig. 1** and **Fig. 2,** respectively. These Figures support the generalization of both ANN models in which the coefficient of determination (R^2) is (95.33%) for model (C) and (98.63%) for model (φ), so it can be inferred that both models are very well agreed with the actual observations.

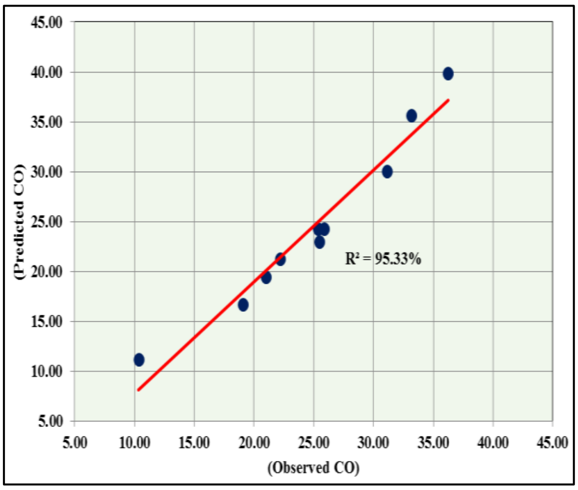

Figure 1. Observed vs. Predicted values of cohesion (C kPa).

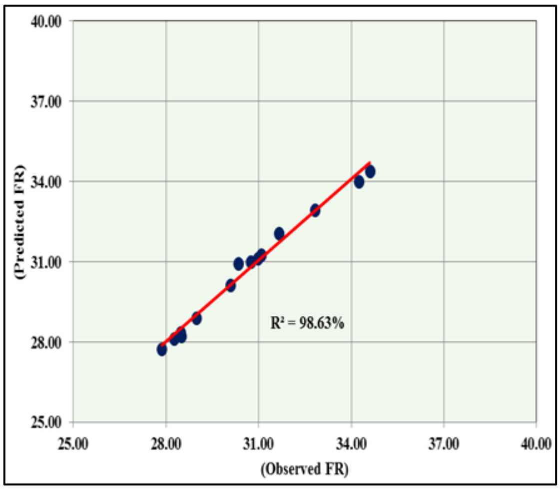

Figure 2. Observed vs. Predicted values of the angle of internal friction (φ).

6. SENSITIVITY ANALYSIS

To identify which of the input variables has the most significant impact on shear strength parameters (C) and (φ), sensitivity analyses were carried out on both ANN models according to **(Al-Janabi, 2006)**. The results of sensitivity analysis of the cohesion model shown in **Table 12** indicate that (γ_d) has the highest effect, followed by (PI), (passing sieve #200), (LL), and (wc) with relative effects of (50.7%), (41.2%), (35.7%) and (34.4%) respectively. The other parameters (P.L.), (gypsum content), (depth) and (e_o) have lower relative effects of (9.5%), (8%), (5.3%) and (0.4%) respectively.

The results of sensitivity analysis of the angle of internal friction model shown in **Table 13** indicate that the gypsum content has the highest effect, followed by (PI), depth, (γd) and (e_o) with relative effects of (95%), (88.9%), (72.3%) and (60.6%) respectively. The other parameters (PL), (wc), passing sieve #200, and (LL) have lower relative effects of (55.1%), (33.1%), (18.6%), and (10.1%) respectively.

Table 12. Sensitivity analysis of the cohesion (C) ANN model

Independent Variable Importance									
	Depth	Gypsum content	L.L.	P.L.	P.I.	Sieve #200	γ_d	WC	e_o
Importance	.019	.028	.125	.033	.178	.144	.351	.121	.001
Normalized Importance	5.3%	8.0%	35.7%	9.5%	50.7%	41.2%	100.0%	34.4%	0.4%

Table 13. Sensitivity analysis of the angle of internal friction (φ) ANN model

Independent Variable Importance									
	Depth	Gypsum content	L.L.	P.L.	P.I	Sieve #200	γ_d	WC	e_o
Importance	.167	.187	.019	.103	.178	.035	.136	.062	.114
Normalized Importance	88.9%	100.0%	10.1%	55.1%	95.0%	18.6%	72.3%	33.1%	60.6%

7. CONCLUSIONS

As a result of this research, the following conclusions can be drawn:

- The developed models have the ability to predict shear strength parameters (C and φ) for gypseous soils with good reliability. Sensitivity analysis of the first model indicated that dry unit weight and plasticity index have the most significant effect on the predicted cohesion. While in the second model, the results indicated that the gypsum content and plasticity index have the most significant effect on the predicted angle of internal friction.
- The validity and generalization of both models were met by testing them using the statistical validation measures (MPE, RMSE, MAPE, AA%, R, and R^2). In which (R^2) for ANN models (C) and (φ) was found to be (95.33%) and (98.63%), respectively.
- Basic soil properties such as gypsum content, dry unit weight, water content, liquid limit, plastic limit, plasticity index, passing sieve #200, and initial void ratio in addition to depth were found to have different influences on shear strength parameters (C and φ) of gypseous soil.
- The obtained mathematical equations provide a quick method to estimate shear strength parameters (C and φ) for gypseous soils based on basic soil properties.

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