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PREDICTION OF COLLAPSE POTENTIAL FOR GYPSEOUS SANDY SOIL USING ANN TECHNIQUE

AHMED M. NAJEMALDEN[1,2,*], SALAH W. IBRAHIM[2], MAHMOOD D. AHMED[3]

[1]Duhok Polytechnic University, Duhok, Iraq
[2]Civil Engineering Department, University of Mosul, Mosul, Iraq
[3]Civil Engineering Department, University of Baghdad, Baghdad, Iraq
*Corresponding Author: ahmed.najm@dpu.edu.krd

Abstract

The present study illustrates the efficiency of the Artificial Neural Network to model the relationship between the collapse potential of gypseous sandy soil with the soil parameters. Sandy soils were taken from four different regions in Iraq to make 180 samples with different properties. The laboratory program involved the estimation of the collapse potential using the single oedometer apparatus. Seven soil parameters such as gypsum content, specific gravity, initial dry unit weights, initial degree of saturation, initial voids ratio, initial water content, and percentage passing sieve #200 (0.074 mm) were determined on the soils. A backpropagation neural network process was utilized in this research. The analysis of relative importance showed that the specific gravity and gypsum content were the most effective parameters than other inputs. The correlation coefficient R-values of collapse potential dataset of ANN model were found to be 0.998 for each training and testing stages. The results demonstrated the authenticity of utilizing the Artificial Neural Networks as a successful manner for producing the values of collapse potential of the gypseous sandy soils.

Keywords: Artificial neural network, Collapse potential, Gypseous soil, Parametric study, Sensitivity analysis.

1. Introduction

The term gypsum soil ($CaSO_4.2H_2O$) refers to the soil containing the gypsum in its components. They occupy most districts of the world, particularly in the arid and semi-arid region. They cover 30% of the Iraqi area with a different percentage in its gypsum content occasionally the gypsum content is more than the soil content [1, 2]. From the point of view of geotechnical engineering, the soil can be known as a gypsum soil when such soil contains enough percent of gypsum that can alter the properties of this soil. Generally, the gypsum soil is stiff when it is dry, however, most of this stiffness is lost and becomes more compressible upon wetting.

Generally, any soil under the load will settle. The quantity of the settlement depends on the type of soil and on the amount of the load applied. However, after a certain time, such settlement will cease. However, in some types of soils, such as gypseous soil, which has a metastable structure and its particles are bonded together by dissolvable minerals and with or without a small amount of clay. These soils are fairly strong when they are in the unsaturated state. However, when exposed to more wetting, the excess water will weaken or damage the bonds, causing shear failure and consequently an additional settlement. This type of settlement is called collapse [3].

The collapsibility behaviour of gypseous soils was studied by many investigators and they agreed with the term "collapse potential", which suggested by Jennings and Knight [3] for use in the studies of the soil’s collapsibility [4-13]. To measure the collapse potential of the soil, an oedometer sample can be used with simple alteration in the process of the test. Besides the time and effort consuming, this test requires the use of undisturbed samples that are difficult to obtain, especially the sandy soil samples.

Artificial Neural Network (ANN) is a useful technique and may be suitable for this purpose. To date, this technique is being utilized successfully in a wide domain of the geotechnical engineering applications. As examples, it has been used in the prediction of the bearing capacity of footings and pile foundations and its settlement [14-17]. Several investigators have utilized the ANN in predicting the liquefaction potential of soils such as Najjar and Ali [18], Farrokhzad et al. [19]. Also, Artificial Neural Networks have been utilized with highly efficient in predicting compaction parameters [20, 21], as well as in the estimation of the suction capacity [22]. Moreover, the ANNs have been used successfully in the mapping of the soil layers [23].

One of the objectives of this research is to explore the reliance on the use of Artificial Neural Networks (ANN) to obtain an important parameter in collapsible soil, i.e., the collapse potential of gypseous sandy soils founded by single oedometer instrument. Moreover, providing a mathematical equation to use in the computation of Collapse Potential value of such soils, and work a sensitivity study to define the impact percentage of every input variable on the collapse potential.

2. Artificial Neural Networks

Artificial Neural Networks are a modeling of artificial intelligence that tries to imitate the kind of manner of the human brain and nervous system [24, 25]. The architecture and operation of ANNs were explained by several investigators such as [26, 27].

ANN architectures are created by three or more layers, which involve an input layer, a number of intermediate layers named hidden layers and an output layer, where neurons are jointed to each other with adjustable weighted interconnections. This ANN structure is usually referred to as a full layer of multiple layers of interlaced receptors. Furthermore, there are also thresholds (bias), associated only with neurons in output and hidden layers, with modifiable weighted connections. The appropriate number of neurons in every layer will be established depending on the type of the problem.

The back-propagation (BP) algorithm is the most common training algorithm for multi-layered feed-forward networks, which is widely utilized in the scope of geotechnical engineering [24]. The BP algorithm consists mainly of two phases. The first is the feed-forward phase where the activation processes are transmitted from the input layer to the output layer. The second is called backward phase, in which, the error detected between the target values and the predicted values in the output layer are propagated backwards in order to update the values of weight and bias of the neurons. This process continues until the error becomes less than the value of the error goal. The inputs and the outputs database for the training and testing should be initialized before training a network [28].

The network contains N inputs and M neurons in the hidden layer with specified B fed as a bias for each neuron. Observe that the outputs of every middle layer are the inputs for the next layers. And hence, if X is the input and A is the output of the hidden layer then Y becomes the production for the output layer. This indicates that the latest output Y of the network will be formed from the outputs of each neuron of the hidden layer and they can be evaluated by Caglar and Arman [28]:

$$A_j = \sum_{i=1}^{n} f\left(X_i W_{ij} + B_i\right) \tag{1}$$

$$Y = \sum_{j=1}^{m} f\left(A_j W_j' + B_j'\right) \tag{2}$$

The symbol f is the transformation function, which is determined to better fit for the data used, The difference (delta) between the actual and desired behaviour of the network is founded by deducting the output vector 'A' from the desired or target vector 'T'. As specified by the delta rule, the post-trial variation in weight W_{ij} of a connection between the input and output is computed by:

$$\Delta W_{ij} = \eta\left(T_j - A_j\right)X_i \tag{3}$$

After the end of every training epoch, the weights will be calibrated continuously until the amount of difference between the output and target values reach an allowable limit or until all training previously specified number of the iteration are finished.

3. Experimental program

3.1. Soil properties

Four different types of soils (Soil #1 - Soil #4) extracted from various places in Iraq, Table 1, were used in this work. These soils were identified due to reporting of damaged structures in areas close to the sites from which, the soils were taken. The preparatory investigation of these destructions indicated that they were already correlated to soil collapse.

The classification stated in the ASTM [29] demonstrated that all the four soils utilized are poorly graded sand. The general features of these soils are recorded in Table 1.

Table 1. Some physical properties of tested soils.

Index properties	**Soil**			
	#1	**#2**	**#3**	**#4**
C_u	3.89	3.68	3.32	3.88
C_c	0.87	0.84	0.67	1.03
$\gamma_{d\,max}$ **kN/m³**	18	18.7	19.5	19.2
OWC, %	8.15	11	8.15	10.3
Sand, *S* %	96.38	95.83	98	94.69
Fines, *F*%	3.62	4.17	2	5.31
Soil classification	*Sp*	*Sp*	*Sp*	*Sp*
Region	Tikret	Abu Greeb1	Abu Greeb2	Anukhayb

3.2. Sample preparation

In the preparation of any sample, one of the values (11-15) KN/m³ was taken as the value of initial dry unit weight (γ_d), and one of the values (2, 4, 6, 8, 10) % was taken as the value of the initial water content (ω_o). According to the chosen value of the initial dry unit weight, a quantity of the dried soil was weighed corresponds to the size of the consolidation ring (diameter 76 mm, height 20 mm).

This amount of dried soil was mixed with a computed quantity of water to yield the predetermined initial water content (ω_o) and then kneaded by the hand to produce a better homogenous mixture. The moist soil was compressed into the ring of the oedometer and a pressure wedge was utilized on the surface of the specimen. Then, the sample was compacted statically to perfectly fit the ring. It is being noted that the method of the single-oedometer test was used in this program, and four identical samples were tested in each condition. Finally, the evaluate collapse potential of the four samples were averaged to attain a single representative data point.

3.3. Test program

The program of the collapse test composed of single-oedometer tests on samples fitted immediately in the rings of the oedometer. A total of 4 test sets according to the soil type (Soil #1 - Soil #4) were carried out where the gypsum content, percentage of passing #200 (0.074 mm), water content, specific gravity, dry unit weight, degree of saturation, and the voids ratio were varied.

The pressure at wetting of 200 kN/m^2 was used in all tests. These tests were performed in a method that in every sets some of the particular properties were changed and the other properties were kept constant. The details about the series of tests are demonstrated in Table 2.

Table 2. Limits of the soils properties were used in the collapse test.

Soil	% pass. #200	*Gs*	*G.C.* %	Initial γ_d kN/m^3	ω_o %	e_o	Initial S_r %
#1	3.62	2.39	55	11-15	2-10	(0.56, 0.67, 0.8, 0.95, 1.13)	4-41
#2	4.17	2.52	30	11-15	2-10	(0.65, 0.77, 0.9, 1.06, 1.25)	4-41
#3	2	2.56	18	11-15	2-10	(0.67, 0.79, 0.93, 1.09, 1.28)	4-41
#4	5.31	2.61	12	11-15	2-10	(0.71, 0.83, 0.97,1.13, 1.33)	4-41

4. Model Methodology

4.1. Data base

Database that was utilized in this research obtained from the information of the collapse potential tests conducted in the soil mechanics laboratory. Datasets of 180 samples were collected and divided randomly. 80% were used to create the model called the training set, while the other 20% of the data was used for testing the model. To generate the *NN* model, seven variables are chosen as inputs. These variables are (percentage passing sieve #200, specific gravity, gypsum content, initial water content, initial dry unit weight, initial voids ratio and degree of saturation), whilst the collapse potential (*Cp*) is the variable in the output layer.

4.2. Pre-processing of data

Data pre-processing is inevitable for verify that every variable takes similar care during the training process. In addition, pre-treatment usually accelerates learning and achieves better convergence. It can be in the form of data transformation, scaling and normalization. Scaling of the output data is necessary, as it must be proportional to the borders of transfer functions exercised in the output stratum [24, 30]. Since the tan-sigmoid is used here as a transfer function Fig. 1, therefore, the range of scaled inputs and the output will be in the (-1 to +1).

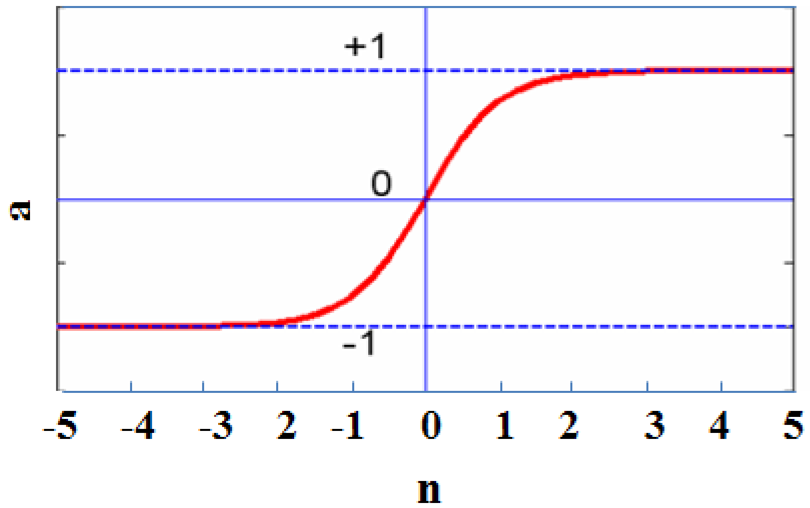


Fig. 1. Tangent sigmoid transfer function [31].

4.3. Model architecture, optimization and stopping criteria

In this study, a multi-layered feed-forward neural network with the back-propagation algorithm was relied on to predict the values of the collapse potential. ANN was developed utilizing the widely known software package [MATLAB R2015a] [31].

Levenberg-Marquardt (LM) back propagation algorithm is a powerful improvement technique, which was inserted in the neural network studies because it supplied methods that speed the process of the training and convergence of the algorithm. Since we will utilize the mean square error (MSE) as a performance index for neural net training, therefore the LM is the appropriate algorithm can be used [32, 33].

In the beginning, the experimental database was divided arbitrarily into training data group (80%) and testing data group (20%). The first group (80%) had employed to train various network structures. The remaining group (20%) was utilized to test the predictability of each ANN model trained. Then the network model was constructed. The architecture of our ANN model composed of three layers. The first layer named the input layer, which has seven nodes representing input parameters. The layer that lies in the middle is called the hidden layer and contains three nodes here. Finally, the last layer termed the output layer and it had here unique node that provided the collapse potential of the soils. The convergence in the training process is achieved by reducing the mean squared error (MSE) within training iterations and observing the general performance for the trained stages by comparing the results. The configuration of the final ANN model with its Properties illustrated in Fig. 2 and Table 3.

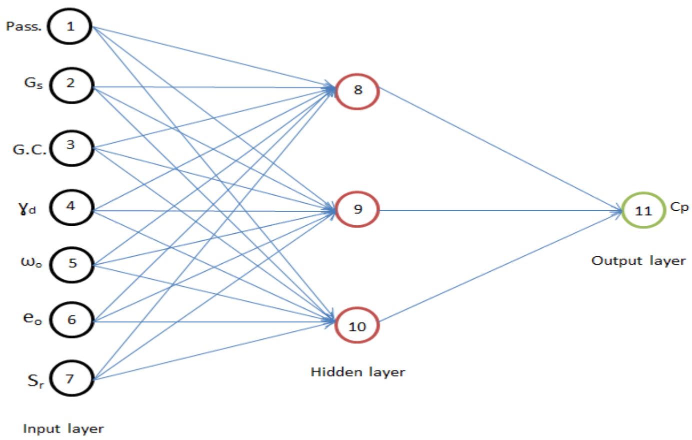


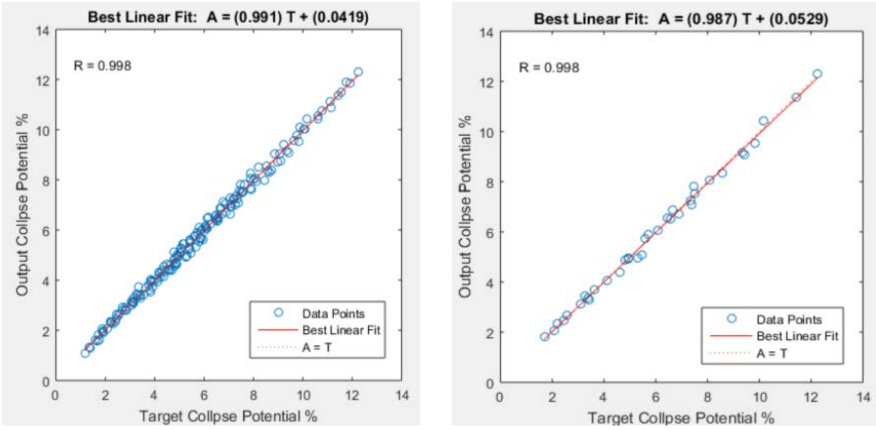
Fig. 2. Architecture of the model.

Table 3. Properties of ANN model.

Properties	Configuration
Architecture	7-3-1
Activation function	Tan sigmoid
Learning algorithm	Levenberg-Marquardt (LM)
Mean Squared Error (MSE)	0.0005

Figure 3 shows the comparison between the results of single collapse potential tests and the neural network prediction of collapse potential for training and testing stages of the ANN model with 3 hidden nodes.

As appear in this figure, this comparison shows that there is a good agreement between the ANN and single collapse test results. The correlation coefficient R-values of collapse potential dataset of ANN model were found to be 0.998 for each training and testing.



(a) Training stage. **(b) Testing stage.**

Fig. 3. Comparison between the results of single collapse potential tests (target) and the neural network prediction of collapse potential (output).

5. Results and Discussion

5.1. Model equation

After ANN training, an equation of the model can be created using connection weights and threshold levels tabulated in Table 4 as model parameters.

Table 4. Weights and biases levels of the ANN model.

Nodes	W_{ji} (Weights from node i in the input layer to node j in the hidden layer)							**Hidden layer bias θ_j**
	***i* = 1**	***i* = 2**	***i* = 3**	***i* = 4**	***i* = 5**	***i* = 6**	***i* = 7**	
***j* = 1**	0.41	0.43	-0.49	-0.07	-1.44	0.44	-1.18	-1.917
***j* = 2**	0.12	-0.71	-0.74	-1.50	-0.25	-0.90	0.22	-0.541
***j* = 3**	-0.16	1.68	1.22	-0.14	-0.29	0.58	0.96	0.845
Nodes	W_{ji} (Weights from node i in the hidden layer to node j in the output layer)							**Output layer bias θ_j**
	***i* = 8**	***i* = 9**	***i* = 10**					
***j* = 4**	0.05	1.08	-0.79					0.605

The mathematical equation for predicting collapse potential (C_{Pn}) of single oedometer can be expressed as [30, 34]:

$$C_{Pn} = f_{sig}\{\theta_4 + \sum_{j=1}^{h}[W_{(j+7)4} \times f_{sig}(\theta_j + \sum_{i=1}^{n} W_{ij}X_i)]\} \quad (4)$$

where, C_{Pn} is the normalized collapse potential (C_p value in the range -1 to 1 for this state), and X_i input variable i, which normalized in the range (-1, 1). Also, by utilizing the results of the weights and thresholds as per LMNN listed in Table 4, the following equations can be established to eventually obtain a correlation of the collapse potential for the gypseous sandy soils with the input variables.

$$A_j = \sum_{j=1}^{h}(\theta_j + \sum_{i=1}^{n} W_{ij} X_i) \quad (5)$$

$$B_j = \sum_{j=1}^{h}[W_{(j+7)4} \times f_{sig}(A_j) \quad (6)$$

$$C_1 = \theta_4 + \sum_{j=1}^{h}[B_j] \quad (7)$$

$$C_{Pn} = f_{sig}(C_1) \quad (8)$$

$$A_1 = -1.917+0.41(\%Pass.)+0.43(Gs)-0.49(G.C.)$$

$$-0.07(\gamma_d)-1.44(\omega_o)+0.44(e_o)-1.18(Sr) \quad (9)$$

$$A_2 = -0.541+0.12(\%Pass.)-0.71(Gs)-0.74(G.C)-1.5(\gamma_d)$$

$$-0.25(\omega_o)-0.9(e_o)+0.22(Sr) \quad (10)$$

$$A_3=0.845-0.16(\%Pass.)+1.68(Gs)+1.22(G.C)-0.14(\gamma_d)-0.29(\omega_o)+0.58(e_o)+0.96(Sr) \quad (11)$$

$$B_1 = 0.046 \times \frac{e^{A_1}-e^{-A_1}}{e^{A_1}+e^{-A_1}} \quad (12)$$

$$B_2 = 1.077 \times \frac{e^{A_2}-e^{-A_2}}{e^{A_2}+e^{-A_2}} \quad (13)$$

$$B_3 = -0.788 \times \frac{e^{A_3}-e^{-A_3}}{e^{A_3}+e^{-A_3}} \quad (14)$$

$$C_1 = 0.605+B1+B2+B3 \quad (15)$$

$$C_{Pn} = \frac{e^{C_1}-e^{-C_1}}{e^{C_1}+e^{-C_1}} \quad (16)$$

The value of the normalized collapse potential (C_{Pn}) obtained from Eq. (16) must be denormalized as:

$$C_P = 0.5(C_{Pn}+1)(C_{Pmax}-C_{Pmin})+C_{Pmin} \quad (17)$$

5.2. Sensitivity analysis

Sensitivity analysis is an operation to studying the reason and effect between the inputs and the outputs data set [35]. After training the neural network, it is necessary to recognize the influence of every input parameter individually on the result of the output. Any input channel that produces little value of sensitivity can be supposed as insignificant channel and can be omitted, this will minimizes the difficulty and the time required for the training, and thus, improving network performance, and vice versa. Because the BPNN weight is not eased and directly comprehensible in the shape of a digital matrix, it can be converted to a percentage value by utilizing a simple method proposed by Garson [36]. In this method, the weights of each input parameter will be divided on the sum of all input weights, which produces the relative importance of every input variable to the output variable.

The procedures of this method were also found and applied by many researches [30, 32, 37]. The produced relative importance for every input variable can be seen in Fig. 4. As the figure indicates, the specific gravity and gypsum content had the largest significant impact on the produced collapse potential of single oedometer test with a value of relative importance of 19.69 and 17.35% respectively, then followed by degree of saturation, initial water content, initial voids ratio and dry unit weight with a relative importance of 16.76, 14.57, 13.87 and 12.77% respectively. However, the percentage of passing #200 had less importance than other properties of the soil with a relative importance of 4.99%.

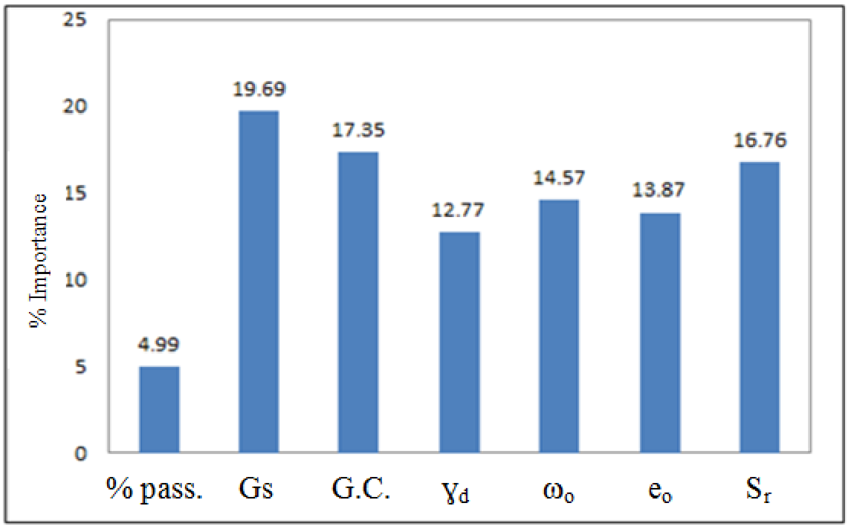


Fig. 4. Relative importance.

5.3. Parametric study

Ease implementation of the parametric study is one of the advantages of neural networks models, where it can be done by changing only one of the input parameters and stabilized all remain input parameters to fixed values. During parametric studies, the model's performance can be verified in simulating the physical behaviour of collapsible sandy soils, due to the variations in the values of some parameters.

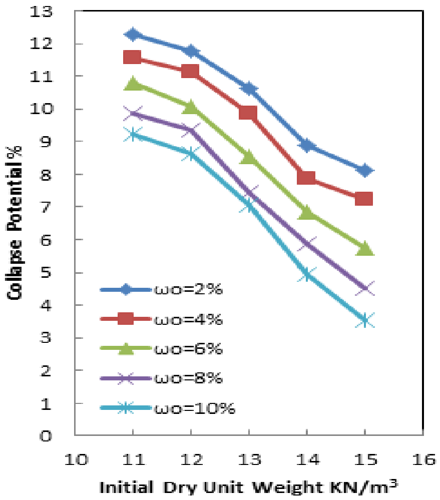
5.3.1. Effect of initial dry unit weight with initial water content

The correlation among the collapse potential with the initial water content (ω_o) and dry unit weight (γ_d) are illustrated in the Figs. 5 and 6. The domain of initial water content values was 2-10%, while the domain of dry unit weight values was (11 to 15) kN/m^3.

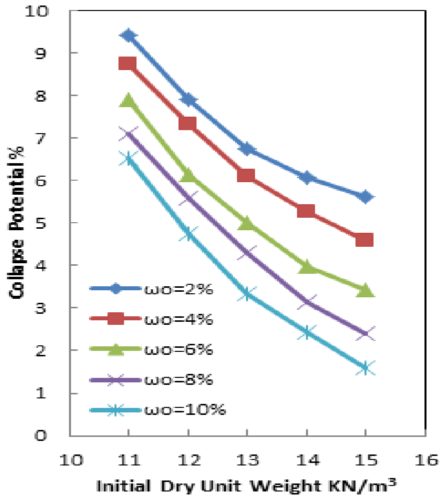
As presented in such figures, the collapse potential is decreasing with the increase of dry unit weight and with increasing of initial water content, keeping other parameters constant. Same correlations were reached by Al-Ani and Seleam [38], Basma and Kallas [39], Al-Mashhadani [37] and Fattah and Dawood [40].

As shown in Fig. 5, the amount of reduction in the collapse potential as a result of the increase in the value of initial water content from 2% to 10% will generally appear a few increases with the increment in the value of dry unit weight from (11 to 15) kN/m^3.

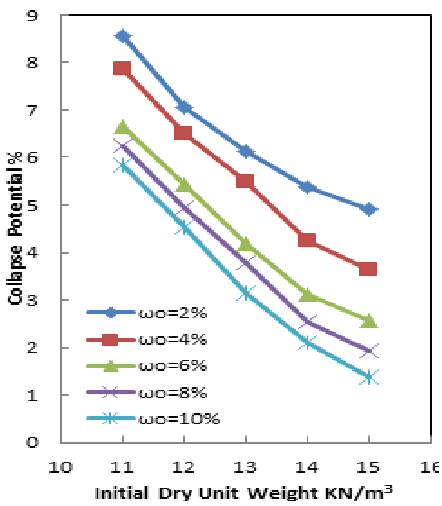
However, in Fig. 6, since the curves are parallel in the most of its portions, therefore, for all type of soil used here, the amount of reduction in the collapse potential resulting from the increasing of the dry unit weight from 11 to 15 kN/m^3 will not be obvious with initial water content increasing from 2% to 10%.



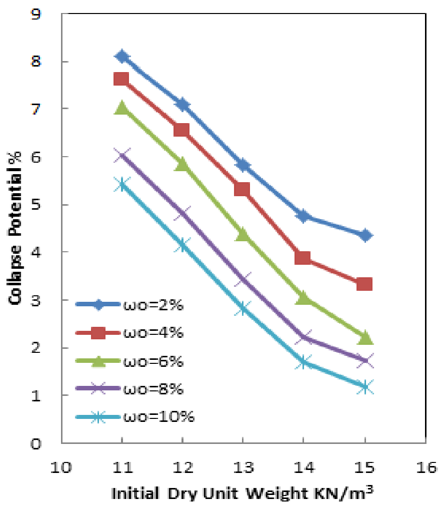
(a) Soil #1.



(b) Soil #2.

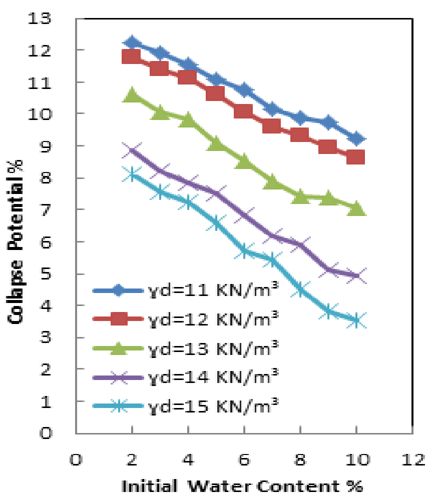


(c) Soil #3.

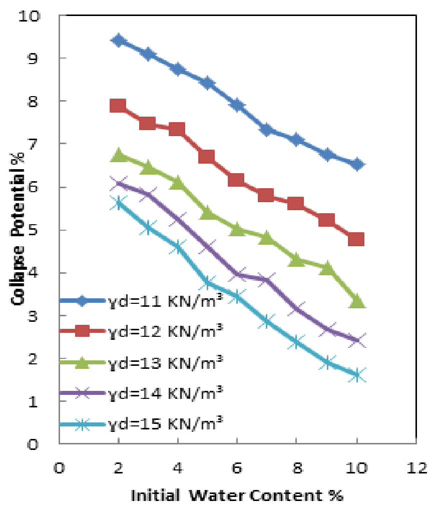


(c) Soil #4.

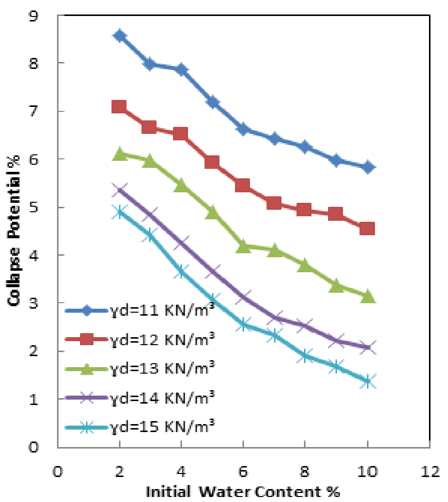
Fig. 5. Effect of initial dry unit weight and initial water content on the collapse potential.



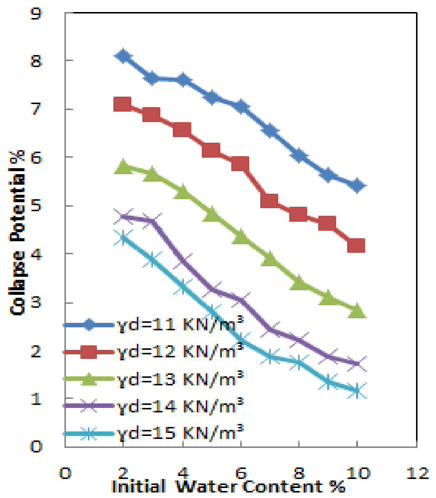
(a) Soil #1.



(b) Soil #2.



(c) Soil #3.



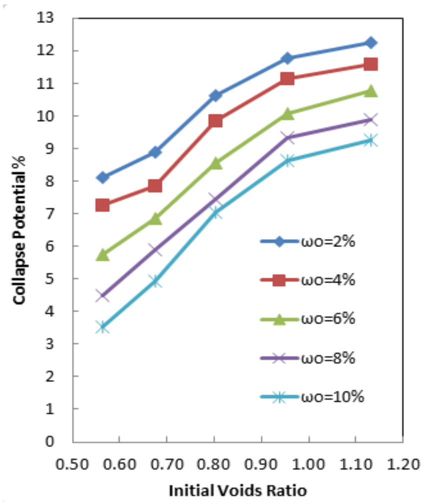
(c) Soil #4.

Fig. 6. Effect of initial water content and initial dry unit weight on the collapse potential.

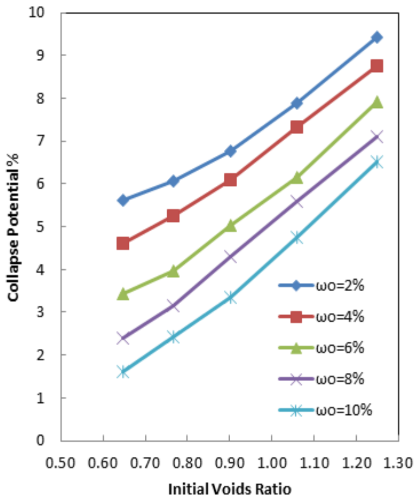
Effect of initial voids ratio with initial water content

Influence of the initial voids ratio (e_o) and Initial water content (ω_o) on the collapse potential of the gypseous sandy soil is plotted in Fig. 7. Limits of initial water content values were used in this parametric study are 2-10%.

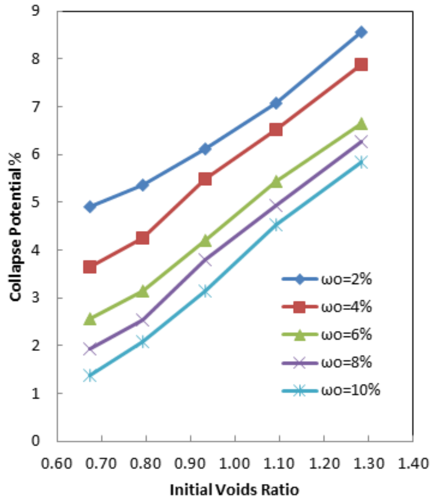
It can be observed from such figure that the collapse potential will increase as a result of the increase in the voids ratio, this is consistent with results of Al-Gabri [41], Al-Mashhadani [37] and Fattah and Dawood [40]. Also, from the same figure, it could be seen that if initial water content decreases, this will lead to an increase in the collapse potential.



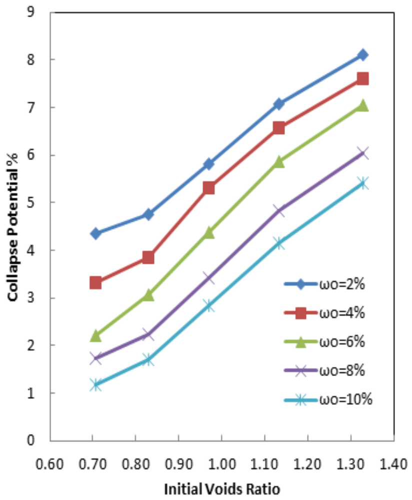
(a) Soil #1.



(b) Soil #2.



(c) Soil #3.



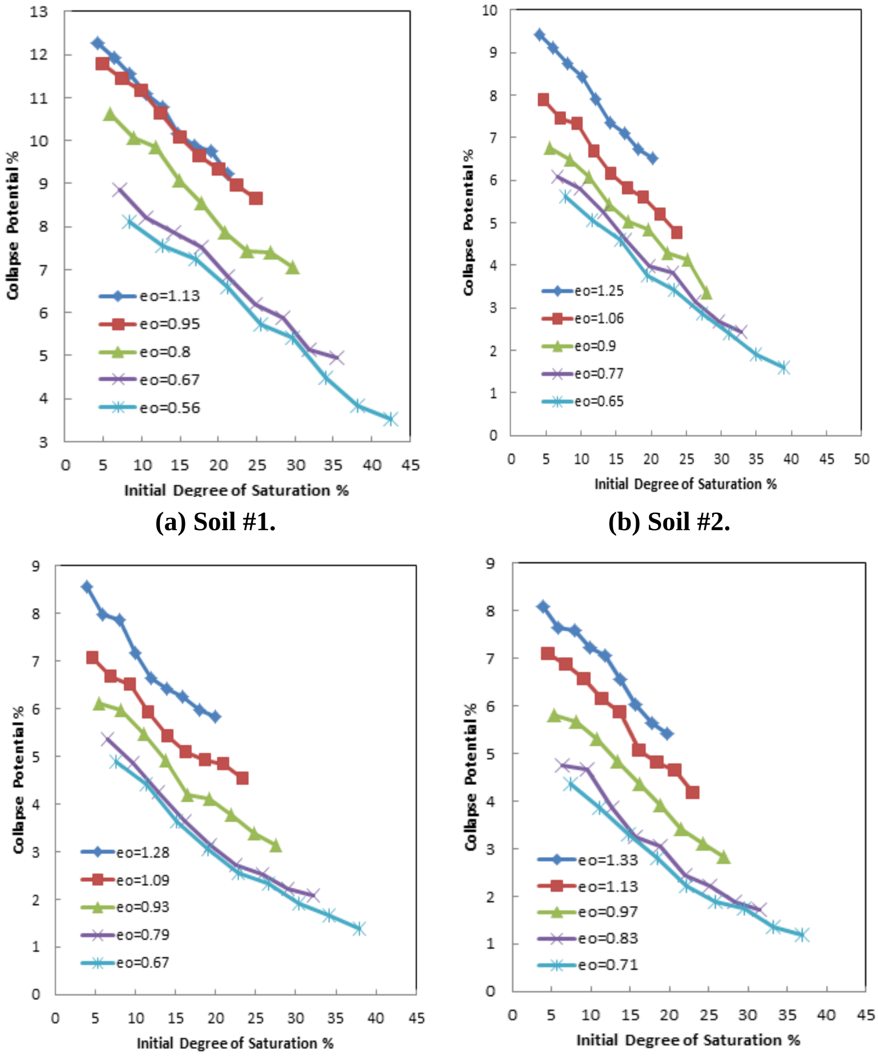
(c) Soil #4.

Fig. 7. Effect of initial voids ratio and initial water content on the collapse potential.

Effect of initial degree of saturation with initial voids ratio

Figure 8 illustrated how the collapse potential of the gypseous sandy soil was affected by the variation in the initial degree of saturation and the variation in the initial void ratio.

For the curve of the same value of initial voids ratio, a higher collapse potential can be correlated with lesser amounts of a degree of saturation, and vice versa, this corresponds to what Fattah and Dawood [40] found. While, for the constant value of the degree of saturation, the gypseous sandy soil will have a higher collapse potential when the initial voids ratio is higher, and vice versa.



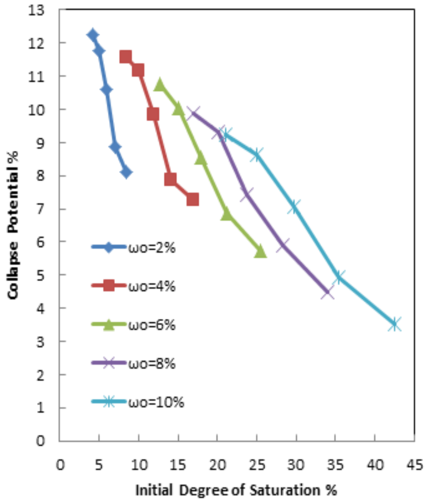
(a) Soil #1. **(b) Soil #2.**

(c) Soil #3. **(c) Soil #4.**

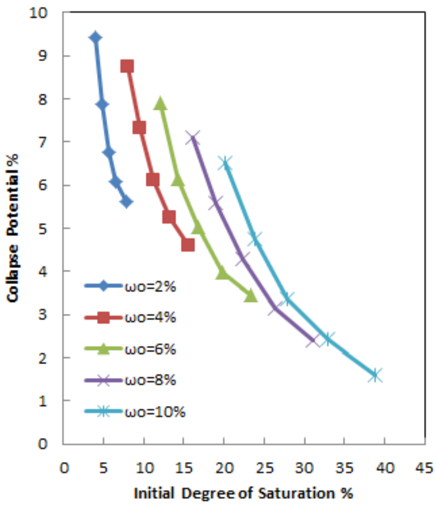
Fig. 8. Effect of degree of saturation and initial voids ratio on the collapse potential.

Effect of initial degree of saturation with initial water content

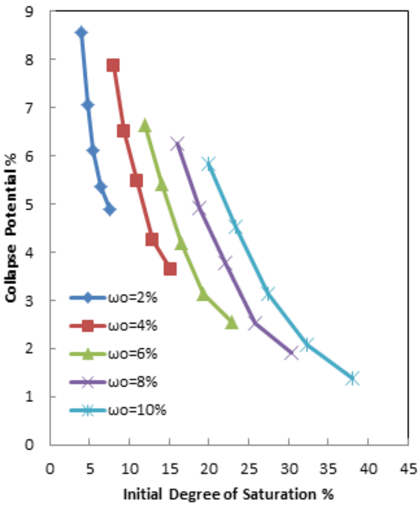
Each curve shown in Fig. 9 represents the correlation between the collapse potential with the initial degree of saturation of a specific value of the initial water content. Note that these curves have a great slope, thus, when the initial degree of saturation is increased, the collapse potential of gypseous sandy soil will largely decrease. This implies that the influence of the initial degree of saturation on collapsibility potential of the gypseous sandy soil is large and more than the effect of other parameters used in this study except for specific gravity and gypsum content (see Fig. 4). In addition, Basma and Tuncer [42], Houston et al. [43] stated that the initial degree of saturation is regarded as one of the key factors controlling the collapse behaviour of unsaturated soil.



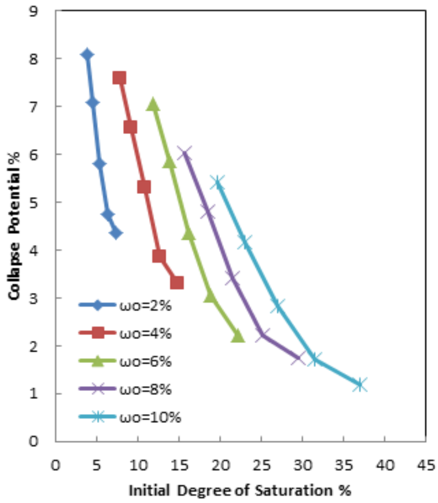
(a) Soil #1.



(b) Soil #2.



(c) Soil #3.



(c) Soil #4.

Fig. 9. Effect of initial degree of saturation and initial water content on the collapse potential.

6. Conclusions

This study has identified the soils properties and their relative important contribution in using ANN to predict the collapse potential of gypseous sandy soils. Building on the information from this research, the following points can be drawn:

- ANN can obtain the collapse potential of gypseous sandy soil with accuracy in the field of data used to develop the ANN model.
- The obtained mathematical equation can give a quick method to obtain the value of the collapse potential of gypseous sandy soil by utilizing only the products of the basic soil tests.

- Using a tan-sigmoidal transformation, the most appropriate network architecture attained consisted of a three-layer back-propagation model, seven input neurons, a single hidden layer involving three neurons, and one output layer containing one neuron.
- As per the sensitivity analysis, the inputs variables can be arranged according to their relative importance as follows: specific gravity, gypsum content, degree of saturation, initial water content, initial voids ratio, dry unit weight and finally the percentage of passing #200.
- The results of the parametric study displayed that the value of collapse potential of gypseous sandy soil increased with the reduction in the values of initial water content, dry unit weight as well as the degree of saturation, and also with the increase in the voids ratio.

Nomenclatures

B_i	Biases between input and hidden layers
B_j'	Biases between hidden and output layers
Cc	Coefficient of curvature
C_P	Collapse potential, %
C_{Pn}	Normalized collapse potential, %
C_{Pmax}	Maximum value of collapse potential in the data collection, %
C_{Pmin}	Minimum value of collapse potential in the data collection, %
Cu	Coefficient of uniformity
e_o	Initial voids ratio
f_{sig}	Sigmoid transfer function
G.C.	Gypsum content, %
Gs	Specific gravity
h	Number of nodes existing in the middle layer
m	Number of hidden neurons
n	Number of input variables
OWC	Optimum water content, %
S_r	Degree of saturation, %
X_i	Input variable i, which normalized in the range (-1, 1)
W_{ij}	Connecting weight of the i^{th} input variable with j^{th} node of middle layer
W_j'	Connection weights between hidden and output layers
$W_{(j+7)4}$	Connecting weight between $i = (j+7)^{th}$ node of the middle layer with the single output node

Greek Symbols

γ_d	Dry unit weight, kN/m^3
γ_{dmax}	Maximum dry unit weight, kN/m^3
η	Learning rate
θ_4	Bias in the output layer
θ_i	Bias at the j^{th} node in middle layer
ω_o	Initial water content, %

Abbreviations

LMNN	Levenberg-Marquardt Neural Network

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