Forecasting the Compressibility Parameters of Gypseous Soil using Artificial Neural Networks

Dunia S Al-zubaidy1,3, Khalid R Aljanabi2,4 and Zeyad S M Khaled1,5
1 College of Engineering, AL-Nahrain University, Baghdad, Iraq
2 College of Engineering, University of Anbar, Anbar, Iraq
3 Corresponding Author, dunia_salem@yahoo.com, 4 kr_aljanabi@uoanbar.edu.iq, 5 zeyadkhaled@eng.nahrainuniv.edu.iq

Abstract. To ensure safe design of structures against settlement, it is necessary to determine the compressibility parameters of the underneath soil especially compression and rebound indices. In this paper, an approach to forecast the compressibility parameters of gypseous soils based on index parameters was developed using Artificial Neural Networks technique. Two equations were developed to estimate compression and rebound indices using back propagation algorithm to train multi-layer perceptron, in which good agreements were achieved. The input parameters used were: the depth, gypsum content, liquid limit, plastic limit, plasticity index, passing sieve No.200, dry unit weight, water content and initial void ratio. Two output parameters were determined including compression index and rebound index. A parametric study was also conducted to investigate the generalization and robustness of both models. The findings indicate that both models were reliable within the range of utilized data. It was found that gypsum content has the highest effect on the compressibility index followed by water content, plasticity index, dry unit weight and plastic limit, while other parameters have lower effect. The gypsum content has the highest effect again on the rebound index followed by passing sieve No.200, initial void ratio, plastic limit and plasticity index, while other parameters have lower effect.

1. Introduction
When gypsum is present in the soil leading to any change in its behaviour, it is referred to as gypseous soil. Gypseous soil is very common in Iraq covering vast areas of middle and south territories of the country. The geotechnical properties of this soil are highly affected by gypsum content which makes the determination of its geotechnical parameters more complex and expensive [1]. Gypseous soil is usually stiff when it is dry; however, most of its stiffness is lost and it becomes more compressible upon wetting [2]. This phenomenon causes foundation failure when such soil is subjected to percolation of water and then dissolution of gypsum [3].

The determination of the geotechnical parameters is usually experimentally done using standard tests. This might be costly and takes a lot of time when dealing with vast areas especially where gypseous soil exists [4]. A technically acceptable feasible approach is needed to forecast some parameters like compressibility parameters based on easily known soil properties. During the past three decades, many researches have been conducted in Iraq to investigate the effect of gypsum content on the engineering properties of soil. Different results on the effect of gypsum content were grasped. Thus, to cope with this diversity, traditionally built models need to be improved. An alternative promising approach is the Artificial Neural Networks [5].

ANN has been used to predict the bearing capacity and settlement of footings and pile foundations [6]. It has also been used to predict liquefaction potential of soils [7]. Moreover, it has been used to predict
compaction parameters [8]. Furthermore, it has been used to predict the suction capacity [9]. In addition, it has been used in mapping soil layers [10].

Artificial Neural Network (ANN) is one of the modelling techniques that simulate the function of human brain and nervous systems. ANNs learn by example in which an actual measured set of input variables and the corresponding outputs are presented to determine the rules that govern the relationship between them [11]. A typical structure of an ANN consists of a number of artificial neurons (processing elements, nodes or units) that are usually arranged in layers. One input layer, one output layer and one or more intermediate layers (hidden layers). Each node in a specific layer is fully or partially connected to many other nodes via weighted connections. The scalar weights determine the strength of the connections between interconnected nodes. A zero weight refers to no connection between two nodes and a negative weight refers to a prohibitive relationship as shown in Figure (1) [12].

Concerning previous studies on compression (Cc) and rebound indices (Cr), some recent related studies can be summarized as follows:

Al-Qaissy in (1989) found that (Cc) and the total volumetric strain at the end of the one-dimensional compression test decreased as the gypsum content increased. The study also showed that a significant decrease in (Cr) was observed as the gypsum content increases in the soil [13].

Al-Aithawi in (1990) studied the compressibility characteristics of gypseous silty soil obtained from Baiji. The results showed that the soil exhibits low compressibility. Furthermore, little time was required for the completion of primary consolidation. The soil also exhibited secondary compression [14].

Al-Dulaimi in (2004) found that (Cc) and volumetric strain increased as gypsum content of the soil increased. This behaviour is attributed to the fact that the gypsum acts as cementing agent between soil particles of dry samples and thus increases the resistance to deformation [15].

Khan in (2005) studied the compressibility characteristics of compacted soil samples with gypsum contents of (37%) and (56%). The results showed that the shape of e-log pressure curves for compacted samples with higher gypsum content were steeper than the curves of samples with lower gypsum content. It was also noticed that (Cc) and (Cr) had increased with increased compaction effort from standard to modified tests [16].

Kalantary and Kordnaeij in (2012) established many correlations between (Cc) and physical properties for clayey soils in Mazandaran region. Prediction results using ANN proved to be improved by (1-4%) than other correlation techniques using the same data [17].

Kurnaz et al. in (2016) also applied the ANN technique to predict (Cc) using results collected from geotechnical investigations of construction sites in various countries. It was concluded that the ANN technique provided good predictions based on simple physical properties of soil [18].

AL-Tai et al. in (2017) studied the characteristics of cohesive soil consolidation and physical qualities. In which, ANN was used to forecast (Cc) and compression ratio based on basic soil properties. Samples were taken from various sites in Baghdad and two estimation equations were developed [19].

It can be noticed in these previous studies that (Cc) was predicted using five input variables on maximum. Some studies have study the effect of input parameters alone with no prediction equations.
derived. However, in this study two output factors, compression index and rebound index, were determined. Furthermore, nine input parameters were used aiming at more precise results. Therefore the following objectives were aimed at; to develop ANN models providing mathematical equations to forecast the compression index (Cc) and rebound index (Cr) for gypseous soils with various gypsum contents and properties, to perform a parametric study and sensitivity analysis to determine the impact of each soil property input on the compression and rebound indices and to assess the benefits and limitations of the proposed techniques as a practical tool for prediction.

2. Building the ANN Model

Available data on gypseous soils were collected from published articles, theses and dissertations including results of tests conducted on various types of gypseous soils in different territories in Iraq. Fifty cases were found to be convenient to the scope of this study, so their data was utilized in creating the ANN Models using SPSS V23. Two mathematical equations were developed; one to predict the compression index (Cc) and the other to predict the rebound index (Cr) based on primary gypseous soil properties. Nine parameters were used as inputs including: Depth (D), Gypsum content (GC), Liquid limit (L.L.), Plastic limit (P.L.), Plasticity index (P.I.), Passing sieve No.20, Dry Unit weight (γd), Water content (wc), Initial void ratio (e₀). Multilayer perceptron architecture of networks was used in creating the ANN models for both (Cc) and (Cr). Figure (2) shows the optimal ANN model for the compression index (Cc kPa) using sigmoid activation function for the hidden layer and hyperbolic one for the output layer. Figure (3) shows the optimal ANN model for the rebound index (Cr kPa) using sigmoid activation function for both hidden and output layers. The nods on the left side are the aforementioned inputs while the nod on the right side is the aforementioned outputs. The blue lines indicate that the synaptic weight is more than zero.

2.1. Data Processing, Division and Scaling

The compression index (Cc) data were divided into three groups; 27 items for training, 16 for validation and 7 for testing. The rebound index (Cr) data were divided into three groups too, 37 items for training, 9 for validation and 4 for testing. Subsets were also categorized for further characterization to provide better representation of the data population. Many random combinations of the training, testing, and validation sets were tested until three statistically relevant results have been achieved in which the obtained data sets were always consistent. Tables (1) and (2) list details of the training, testing, and validation sets for the (Cc) and (Cr) ANN models respectively. The statistical parameters considered were the maximum, minimum, mean, standard deviation and range.

![Figure 2. Optimal ANN model for the compression index (Cc).](image)

![Figure 3. Optimal ANN model for the rebound index (Cr).](image)
Table 1. Input and output statistics for the (Cc) ANN model.

| Data set       | Statistical Parameters | Actual Input Variables | Actual Output |
|----------------|------------------------|------------------------|---------------|
|                | Depth m                | Gypsum Content         |               |
| Training       |                         | L.L.                   |               |
| N = 27         | Range: 14.000          | 65.940                 | 62.000        |
|                | Minimum: 1.000         | 4.060                  | 18.000        |
|                | Maximum: 15.000        | 70.000                 | 80.000        |
|                | Mean: 3.111            | 31.046                 | 45.146        |
|                | Std. Deviation: 3.854  | 20.661                 | 15.826        |
|                | Range: 4.200           | 15.220                 | 13.000        |
|                | Minimum: 0.800         | 5.000                  | 40.000        |
|                | Maximum: 5.000         | 22.200                 | 53.000        |
|                | Mean: 1.770            | 13.103                 | 46.143        |
|                | Std. Deviation: 1.051  | 5.542                  | 2.812         |
|                | Range: 4.000           | 57.900                 | 34.700        |
|                | Minimum: 1.000         | 2.600                  | 21.000        |
|                | Maximum: 5.000         | 60.500                 | 55.700        |
|                | Mean: 1.969            | 23.993                 | 41.638        |

| Validation N = 16 | Std. Deviation: 1.087  | 17.255                 | 9.633 |

|                | Sieve No.200           | γa                      | wc                  | c+               | Cc kPa |
|----------------|------------------------|-------------------------|---------------------|-----------------|-------|
| Training       |                         | 11.510                  | 29.900              | 0.695           | 0.047 |
| N = 27         |                         | 11.700                  | 3.600               | 0.200           | 0.016 |
|                |                         | 10.000                  | 23.210              | 0.895           | 0.062 |
|                |                         | 12.310                  | 19.400              | 0.578           | 0.042 |
|                |                         | 15.690                  | 15.690              | 0.917           | 0.053 |
|                |                         | 16.510                  | 16.480              | 1.015           | 0.038 |
|                |                         | 15.400                  | 23.210              | 0.895           | 0.037 |
|                |                         | 11.700                  | 3.600               | 0.200           | 0.016 |
|                |                         | 10.000                  | 23.210              | 0.895           | 0.062 |
|                |                         | 12.310                  | 19.400              | 0.578           | 0.042 |
|                |                         | 15.690                  | 15.690              | 0.917           | 0.053 |
|                |                         | 16.510                  | 16.480              | 1.015           | 0.038 |
|                |                         | 15.400                  | 23.210              | 0.895           | 0.037 |

Table 2. Input and output statistics for the (Cr) ANN model.

| Data set       | Statistical Parameters | Actual Input Variables | Actual Output |
|----------------|------------------------|------------------------|---------------|
|                | Depth m                | Gypsum Content         |               |
| Training       |                         | L.L.                   |               |
| N = 27         | Range: 14.200          | 65.940                 | 62.000        |
|                | Minimum: 0.800         | 4.060                  | 18.000        |
|                | Maximum: 15.000        | 70.000                 | 80.000        |
|                | Mean: 3.111            | 31.046                 | 45.146        |
|                | Std. Deviation: 2.816  | 26.685                 | 45.080        |
|                | Range: 1.500           | 57.900                 | 34.700        |
|                | Minimum: 1.000         | 2.600                  | 21.000        |
|                | Maximum: 5.000         | 60.500                 | 55.700        |
|                | Mean: 1.750            | 28.145                 | 45.425        |
|                | Std. Deviation: 0.289  | 28.300                 | 16.480        |
|                | Range: 1.000           | 39.990                 | 25.500        |
|                | Minimum: 1.000         | 5.010                  | 26.500        |
|                | Maximum: 2.000         | 45.000                 | 52.000        |
|                | Mean: 1.500            | 25.508                 | 39.833        |
|                | Std. Deviation: 0.500  | 13.959                 | 7.632         |

|                | Sieve No.200           | γa                      | wc                  | c+               | Cc kPa |
|----------------|------------------------|-------------------------|---------------------|-----------------|-------|
| Training       |                         | 11.510                  | 29.900              | 0.695           | 0.047 |
| N = 27         |                         | 11.700                  | 3.600               | 0.200           | 0.016 |
|                |                         | 10.000                  | 23.210              | 0.895           | 0.062 |
|                |                         | 12.310                  | 19.400              | 0.578           | 0.042 |
|                |                         | 15.690                  | 15.690              | 0.917           | 0.053 |
|                |                         | 16.510                  | 16.480              | 1.015           | 0.038 |
|                |                         | 15.400                  | 23.210              | 0.895           | 0.037 |
|                |                         | 11.700                  | 3.600               | 0.200           | 0.016 |
|                |                         | 10.000                  | 23.210              | 0.895           | 0.062 |
|                |                         | 12.310                  | 19.400              | 0.578           | 0.042 |
|                |                         | 15.690                  | 15.690              | 0.917           | 0.053 |
|                |                         | 16.510                  | 16.480              | 1.015           | 0.038 |
|                |                         | 15.400                  | 23.210              | 0.895           | 0.037 |

Input and output variables were pre-processed by scaling in order to repeat their dimension for the sake of ascertaining that all variables receive equal attention during training. Furthermore, they were made proportional to the limits of the transfer features used in hidden and output layers for sigmoid transfer function within (0.0) to (1.0) values. The scaled value \( x_a \) for variable \( x \) was calculated using equation (1).

\[
x_a = \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})}
\]

where:
- \( x \): Original value,
- \( x_{\text{max}} \) and \( x_{\text{min}} \): Actual maximum and minimum values.

2.2. Equations Generation

The low number of connection weights obtained for the (Cc) and (Cr) optimal ANN models enable each network to be translated into relatively simple formula. The connection weights and threshold levels are summarized in Tables (3) and (4).
Table 3. Parameter Estimates for the (Cc) ANN optimal model.

| Predictor               | Predicted | Hidden Layer 1 | Output Layer |
|------------------------|-----------|----------------|--------------|
|                        | H(1:1)    | H(1:2)         | Cc           |
| (Bias)                 | -.553     | -.140          |              |
| Depth (m)              | -.189     | .369           |              |
| Gypsum content         | -1.913    | .352           |              |
| L.L.                   | .146      | -.581          |              |
| P.L.                   | -.731     | -.291          |              |
| Input Layer            | P.I.      | 1.259          | -.075        |
|                       | Passing Sieve No.200 | -.203 | -.111 |
| γd                     | .889      | -.462          |              |
| wc                     | 1.452     | -.881          |              |
| e₀                     | -.288     | -.422          |              |
| Hidden Layer 1         | H(1:1)    | H(1:2)         | .1032        |
|                        | 1.032     | 2.971          | .1032        |
|                        | H(1:1)    | H(1:2)         | -.661        |

The predicted (Cc) is expressed as follows:

\[(Cc)_{\text{act}} = \text{Tanh} \big( 1.032 + 2.971 \times h_{1} - 0.661 \times h_{2} \big) \]  

where:

\[ h_{1} = \frac{1}{1 + e^{\gamma_{d}}} \]  
\[ h_{2} = \frac{1}{1 + e^{\gamma_{d}}} \]

While the predicted (Cr) is expressed as follows:

\[(Cr)_{\text{act}} = \frac{1}{(1+e)^{0.184 + 0.093}} \]  

where:

\[ h_{1} = \frac{1}{(1+e)^{0.184 + 0.093}} \]  
\[ h_{2} = \frac{1}{(1+e)^{0.184 + 0.093}} \]

Table 4. Parameter Estimates for the (Cr) ANN optimal model.

| Predictor               | Predicted | Hidden Layer 1 | Output Layer |
|------------------------|-----------|----------------|--------------|
|                        | H(1:1)    | H(1:2)         | H(1:3)       | Cr |
| (Bias)                 | .232      | .412           | .414         | .286 |
| Depth (m)              | .400      | .854           | 1.404        | -.2659 |
| Gypsum content         | 1.740     | -.5766         | -4.756       | 1.111 |
| L.L.                   | -.977     | 3.334          | 3.039        | -.286 |
| P.L.                   | -.702     | 3.179          | 2.622        | 1.111 |
| Input Layer            | P.I.      | 1.259          | -.075        | -.2659 |
|                       | Passing Sieve No.200 | -.203 | -.111 |
| γd                     | .889      | -.462          |              |
| wc                     | 1.452     | -.881          |              |
| e₀                     | -.288     | -.422          |              |
| Hidden Layer 1         | H(1:1)    | H(1:2)         | H(1:3)       |    |
|                        | .232      | .412           | .414         |    |
|                        | .400      | .854           | 1.404        |    |
|                        | 1.740     | -.5766         | -4.756       |    |
|                        | -.977     | 3.334          | 3.039        |    |
|                        | -.702     | 3.179          | 2.622        |    |
|                        | 1.259     | -.075          | -.2659       |    |
|                        | -.203     | -.111          |    |

The predicted (Cc) is expressed as follows:

\[(Cc)_{\text{act}} = \frac{1}{1 + e^{\gamma_{d}}} \]

where:

\[ h_{1} = \frac{1}{(1+e)^{0.184 + 0.093}} \]  
\[ h_{2} = \frac{1}{(1+e)^{0.184 + 0.093}} \]
The results of the (Cc) model are shown in Figures (2) to (9). It can be noticed that the physical parameters of soil have significant effects on compressibility. The value of the compressibility index reduced as the soil gypsum content increased. Figure (2) shows that the depth has no significant effect on the compressibility index. Figure (3) shows that the liquid limit has no significant effect on the compressibility index too. Figure (4) shows that the plastic limit do affect the value of compressibility index. This effect is higher when the soil has higher gypsum content. Figure (5) shows that soil with high plasticity index mostly has lower compressibility index. Figure (6) shows that the value of passing sieve No.200 test has less influence on the compressibility index than other parameters. Figures (7) and (8) show that the dry unit weight and the water content do affect the compressibility index in the same way that the plasticity index does. It is noticed that when the water content, dry unit weight or plasticity index increase, the compressibility index tend to decrease. Figure (9) shows that the reduction in the compressibility index is higher for soil with higher gypsum content despite the value of void ratio which mostly have no effect on the value of compressibility index.

On the other hand, Figures (10) to (17) shows that the value of the rebound index decreases as the soil gypsum content increase. Figure (10) shows that the depth has no significant effect on the rebound index. Figure (11) shows that the liquid limit has no significant effect on the rebound index too. Figure (12) shows that plastic limits do affect the value of the rebound index. This effect is higher when the soil has higher gypsum content. Figure (13) shows that soil with high plasticity index mostly has lower rebound index. Figures (14) and (15) show that the dry unit weight and the water content do affect the rebound index in the same way that the plasticity index does. It is noticed that when the water content, dry unit weight or plasticity index increase the rebound index tend to decrease. Figure (16) shows that the value of passing sieve No.200 test has less influence on the rebound index than other parameters. Figure (17) shows that the reduction in the rebound index is higher for soil with higher gypsum content despite the value of void ratio which mostly does not affect the value of rebound index.

In order to identify which of the input parameters has the greatest impact; sensitivity analysis was carried out using SPSS v23 to identify the relative importance of input variables. The results indicated that the gypsum content has more significant effect on the compressibility index (Cc) than water content, plasticity index, dry unit weight and plastic limit with relative importance of (92.7%), (74.7%), (58.1%) and (37.8%) respectively. While depth, liquid limit, initial void ratio and passing sieve No.200 have lower relative importance of (15%), (14.3%), (12.3%), and (10.3%) respectively.

\[
h_3 = \frac{1}{(1+e)^{x_3}}
\]

\[
x_1 = 0.232 + (0.490 \times \text{depth}) + (1.740 \times \text{gypsum}) - (0.477 \times \text{L.L.}) - (0.702 \times \text{P.L.}) - (0.510 \times \text{P.I.}) - (1.416 \times \text{Sieve}) - (0.505 \times \gamma_d) - (0.042 \times \text{wc}) - (0.951 \times e_0) \quad \ldots \quad (12)
\]

\[
x_2 = 0.412 + (0.854 \times \text{depth}) - (5.766 \times \text{gypsum}) + (3.334 \times \text{L.L.}) + (3.179 \times \text{P.L.}) + (2.633 \times \text{P.I.}) + (8.915 \times \text{Sieve}) + (2.255 \times \gamma_d) + (1.517 \times \text{wc}) + (0.563 \times e_0) \quad \ldots \quad (13)
\]

\[
x_3 = 0.414 + (1.404 \times \text{depth}) - (4.756 \times \text{gypsum}) + (3.039 \times \text{L.L.}) + (2.622 \times \text{P.L.}) + (2.525 \times \text{P.I.}) + (7.494 \times \text{Sieve}) + (2.620 \times \gamma_d) + (1.870 \times \text{wc}) + (0.827 \times e_0) \quad \ldots \quad (14)
\]

\[
(C_{\text{act}} = (C_{\text{inr}} \times \text{range}) + \min \quad \ldots \quad (15)
\]

\[
(C_{\text{act}} = (C_{\text{inr}} \times 0.047) + 0.016 \quad \ldots \quad (16)
\]

3. Results and Discussion

A technique suggested by (Shahin 2003) was used to conduct a parametric study to investigate the generalization ability and robustness of both models. The parametric study was carried out by fixing the input variables to their mean values used for training excluding one parameter. A set of synthetic data between minimum and maximum values used for model training was generated for the excluded input variable that was not set to a fixed value. The synthetic data were generated by increasing their values in increments equal to (25%) of the variable range. This was repeated and the model responses were tested for all input variables.

The results of the (Cc) model are shown in Figures (2) to (9). It can be noticed that the physical parameters of soil have significant effects on compressibility. The value of the compressibility index reduced as the soil gypsum content increased. Figure (2) shows that the depth has no significant effect on the compressibility index. Figure (3) shows that the liquid limit has no significant effect on the compressibility index too. Figure (4) shows that the plastic limit do affect the value of compressibility index. This effect is higher when the soil has higher gypsum content. Figure (5) shows that soil with high plasticity index mostly has lower compressibility index. Figure (6) shows that the value of passing sieve No.200 test has less influence on the compressibility index than other parameters. Figures (7) and (8) show that the dry unit weight and the water content do affect the compressibility index in the same way that the plasticity index does. It is noticed that when the water content, dry unit weight or plasticity index increase, the compressibility index tend to decrease. Figure (9) shows that the reduction in the compressibility index is higher for soil with higher gypsum content despite the value of void ratio which mostly have no effect on the value of compressibility index.

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In order to identify which of the input parameters has the greatest impact; sensitivity analysis was carried out using SPSS v23 to identify the relative importance of input variables. The results indicated that the gypsum content has more significant effect on the compressibility index (Cc) than water content, plasticity index, dry unit weight and plastic limit with relative importance of (92.7%), (74.7%), (58.1%) and (37.8%) respectively. While depth, liquid limit, initial void ratio and passing sieve No.200 have lower relative importance of (15%), (14.3%), (12.3%), and (10.3%) respectively.
Figure 4. Effect of gypsum content and depth on compression index.

Figure 5. Effect of gypsum content and liquid limit on compression index.

Figure 6. Effect of gypsum content and plastic limit on compression index.

Figure 7. Effect of gypsum content and plasticity index on compression index.

Figure 8. Effect of gypsum content and passing sieve No.200 on compression index.

Figure 9. Effect of gypsum content and dry unit weight on compression index.

Figure 10. Effect of gypsum content and water content on compression index.

Figure 11. Effect of gypsum content and initial void ratio on compression index.
Figure 12. Effect of gypsum content and depth on rebound index.

Figure 13. Effect of gypsum content and liquid limit on rebound index.

Figure 14. Effect of gypsum content and plastic limit on rebound index.

Figure 15. Effect of gypsum content and plasticity index on rebound index.

Figure 16. Effect of gypsum content passing sieve No200 on rebound index.

Figure 17. Effect of gypsum content and dry unit weight on rebound index.

Figure 18. Effect of gypsum content and water content on rebound index.

Figure 19. Effect of gypsum content and void ratio on rebound index.
The gypsum content has more significant effect on the rebound index (Cr) than passing sieve No.200, initial void ratio, plastic limit and plasticity index with relative importance of (88.6%), (41.5%), (38.3%) and (27.1%) respectively, while dry unit weight, liquid limit, depth and water content have moderate impact with a relative importance of (26.6%), (26.5%), (18.1%) and (3.8%) respectively.

4. Conclusions
Both models were able to be turned into simple and practical formulae that can be used to predict compression and rebound indices for gypseous soils. The findings of the parametric study using the ANN models built in this study indicate that the model is reliable. Within the range of utilized data, the ANN technique proved the ability to forecast the compression and rebound indices for gypseous soils with reliable accuracy. Based on the results of this research it can be concluded that gypseous soils using Artificial Neural NetworkANN technique proved the ability to forecast the compression and rebound indices for gypseous soils. The findings of the parametric study using the ANN models built in this study indicate that the model is reliable. Within the range of utilized data, the ANN technique proved the ability to forecast the compression and rebound indices for gypseous soils with reliable accuracy. Based on the results of this research it can be concluded that gypseous soils have the highest effect on the compressibility index followed by water content, plasticity index, dry unit weight and plastic limit, while the other parameters; depth, liquid limit, initial void ratio and passing sieve No.200 have lower effect. The gypsum content has the highest effect again on the rebound index followed by passing sieve No.200, initial void ratio, plastic limit and plasticity index, while the other parameters; dry unit weight, liquid limit, depth and water content have lower effect.

5. References
[1] Al-Kaabi F S 2007 State Company of Geological Survey and Mining Report No. 3044 (Baghdad: Iraq)
[2] Al-Shawary A M N 2020 Experimental and numerical behaviour of collapsible gypseous soil with uncertainty properties PhD Thesis (Mosul: Iraq: Department of Civil Engineering, University of Mosul)
[3] Nashat I H 1994 Gypseous Soil Exploitation Proc. Conf. on the Gypseous Soil and Its Effect on Structures (Baghdad: Iraq: Ministry of Housing and Construction: National Center for Laboratories and Construction) pp. 54-63
[4] Al-Neami M A M 2015 Prediction of Unconfined Compressive Strength of Soil Using Artificial Neural Network The 2nd International Conference of Buildings, Construction and Environmental Engineering 3, pp. 223-27 (Beirut: Lebanon)
[5] Al-Janabi K R M 2006 Laboratory Leaching Process Modeling in Gypseous Soils using Artificial Neural Network Ph.D. Thesis (Baghdad: Iraq: Building and Construction Engineering Department, University of Technology)
[6] Shahin M A, Maier H R and Jaksa M B 2002 Predicting Settlement of Shallow Foundations using Neural Networks Journal of Geotechnical and Geoenvironmental Engineering, 128(9), pp. 785-93
[7] Farrokhzad F, Choobbasti A J and Barari A 2010 Artificial Neural Network Model for Prediction of Liquefaction Potential in Soil Deposits Proc. of Fifth International Conference on Recent Advances in Geotechnical Earthquake Engineering and Soil Dynamics (San Diego: California: Missouri University of Science and Technology).
[8] Tenpe A and Kaur S 2015 Artificial Neural Network Modeling for Predicting Compaction Properties Based on Index Properties of Soil International Journal of Science and Research 4(7), pp. 1198-1202
[9] Soner U, Nilay K and Selcuk G 2005 ANN Modelling for Estimation of Suction Capacity Journal of Applied Sciences 4(5), pp. 712-15
[10] Choobbasti A J, Farrokhzad F, Mashaie S R and Azar P 2015 Mapping of soil layers using artificial neural network - case study of Babol Northern Iran Journal of the South African Institution of Civil Engineering 57(1), pp. 59-66
[11] Khaled Z S M, Abid-Al R S and Hasan M F 2017 Modeling the Completion Time of Public School Building Projects Using Neural Networks Civil Engineering Journal 3(12), p. 1268
[12] Shahin M A, Maier H R and Jaska M B 2008 Recent Advances and Future Challenges for Artificial Neural Systems in Geotechnical Engineering Applications (Adelaide: Australia: Department of Civil and Environmental Engineering, University of Adelaide)
[13] Al-Qaissy F F 1989 *Effect of Gypsum Content and its Migration on Compressibility and Shear Strength of the Soil* MSc Thesis (Baghdad: Iraq: Building and Construction Engineering Department, University of Technology)

[14] Al-Aithawi A H 1990 *Time-Dependent Deformation of a Gypseous Silty Soil* MSc Thesis (Baghdad: Iraq: Civil Engineering Department, University of Baghdad)

[15] Al-Dulaimi N S M 2004 *Characteristics of Gypseous Soils Treatment with Calcium Chloride Solution* MSc Thesis (Baghdad: Iraq: Civil Engineering Department, University of Baghdad)

[16] Khan M A J 2005 *Effect of Compaction on the Behaviour of Gypseous Soil* MSc Thesis (Baghdad: Iraq: Civil Engineering Department, University of Baghdad)

[17] Kalantary F and Kordnaeij A 2012 Prediction of Compression Index using Artificial Neural Network *Scientific Research and Essays*, 7, 31, pp. 2835-48

[18] Kurnaz T F, Dagdeviren U, Yildiz M and Ozkan O 2016 Prediction of Compressibility Parameters of the Soils using Artificial Neural Network *Springer Plus*, 5, 1

[19] Al-Taie A J, Al-Bayati A F, Taki Z N M 2017 Compression Index and Compression Ratio Prediction by Artificial Neural Networks *University of Baghdad Engineering Journal* 23(12) pp. 96-106

[20] Shahin M A 2003 *Use of Artificial Neural Networks for Predicting Settlement of Shallow Foundations on Cohesionless Soils* PhD Thesis (Adelaide: Australia: Department of Civil and Environmental Engineering University of Adelaide)