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Prediction of Gypseous Soil Settlement Using Artificial Neural Network (ANN)

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ARTICLE INFO	ABSTRACT
	Gypseous soil exhibits problematic geotechnical engineering properties as they expand, collapse, disperse, undergo excessive settlement, owns a distinct lack of strength, and it is soluble. Gypseous soil has a metastable structure, with dissolvable minerals with a minimal quantity of clay binding the particles together. When gypseous soil unsaturated, they are quite potent. When they are subjected to increased wetness, however, the excess water weakens or damages the bonds, resulting in shear failure and subsequent settlement. Estimating the settlement of shallow foundations on gypseous soils is a difficult topic that is still not fully understood. It is concluded that artificial neural network (ANN) is appeared to be viable solution since it has been successfully used in numerous prognosis applications in geotechnical engineering. In this research, the precipitation values of gypsum soil were predicted under the influence of the applied load using an artificial neural network. The study found that this model is very good in predicting precipitation and found a convergence between the real values and the predict values.

1. Introduction

Gypsum soil is a collapsible soil, which causes major deformations to the buildings that erected on it. The term gypsum soil refers to the soil its content is the gypsum. They cover 30% of the Iraqi area with a different percentage of gypsum content, occasionally; the gypsum content is more than the soil (1). From the point of view of geotechnical engineering, the soil can be known as gypsum soil when such soil contains enough percent of gypsum that can alter the properties of the soil (2). Generally, the gypsum soil is stiff when it is dry most of this stiffness is lost and becomes more compressible upon wetting.

The design of shallow footings on the gypseous soil is subjected to the design of shallow footing on the geotechnical engineering profession and is used to deal with gypseous soil that is subjected to undrained central vertical loading. To satisfy the ultimate limit state, the designer is required to ensure that applied loads remain below the ultimate bearing capacity of the foundation (3). Design for the serviceability limit state requires the settlement of the footing under loads to be small enough to ensure satisfactory performance of the structure. Footing design therefore requires an ability to predict both the ultimate bearing capacity and settlements under working loads.

Objected:

1. To valid the results accuracy by using mean square error and mean absolute error approaches as the performance indices.
2. To evaluate benefits and limitations of the techniques used as a practical method

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for predicting the settlement behaviour of surface foundations.

2. Description of data

Model obtained from the literature and include field measurements of the settlement of shallow foundations and the related information of the foundations and soil. The data covered a wide range of variations in foundations, dimensions and of gypseous soil types and characteristics. The database formation a total of 65 individual cases was studied and collected from the literature review. Where square and rectangular foundations are used.

3. Networks training and testing

It's typical to split the given data into two subsets: a training set for building the neural network model and an independent validation set for estimating model performance in the deployed environment, (4). However, model over fitting may occur if the data is divided into only two subsets. As a result, cross-validation was employed since 70% of the data was used for training and 30%, for testing, and 80 percent of the data was used for training and 20% for testing. For the training set, the training data was further separated into 25 and 50 percent. According to recent research, the way data is separated has a substantial impact on the outcomes (5). ANNs, like other empirical models, are unable to extrapolate beyond their training data range. Figure 1 shows ANN code application in python.

```python
MLPRegressorModel = MLPRegressor(activation='tanh', # can be also identity , logistic , relu
                                 solver='lbfgs',  # can be also sgd , adam
                                 learning_rate='constant', # can be also invscaling , adaptive
                                 early_stopping= False,
                                 alpha=0.0001 ,hidden_layer_sizes=(100, 3),random_state=33)
MLPRegressorModel.fit(X_train, y_train)


#Calculating Prediction
y_pred = MLPRegressorModel.predict(X_test)
#Calculating Mean Absolute Error
MAE_ANN = mean_absolute_error(y_test, y_pred) # it can be raw_values
print('Mean Absolute Error Value is : %.3f' % MAE_ANN)
#Calculating Mean Squared Error
MSE_ANN = mean_squared_error(y_test, y_pred) # it can be raw_values
print('Mean Squared Error Value is  : %.3f' % MSE_ANN)
x_ax = range(len(y_pred))
plt.scatter(x_ax, y_test, s=5, color="blue", label="original")
plt.plot(x_ax, y_pred, lw=0.8, color="red", label="predicted")
plt.legend()
plt.show()
```

Figure 1. Apply artificial neural network model

4. Basic concepts of artificial neural network (ANN)

Artificial neural network is a form of artificial intelligence that attempts to mimic the behaviour of the human brain. Several authors have described the operation of neural networks (6), whereby the typical architecture of artificial neural networks, consists of a number of processing elements or nodes that are arranged in layers (an input layer, an output layer and one or more hidden layers).

An artificial neural network (ANN) is a machine-learning tool that is used to detect dynamic or nonlinear behavior. The artificial neural network, unlike bivariate correlation or

linear regression, employs a multi-layer perceptron comparable to the support vector machine (SVM). Deep Neural Network (DNN) and Linear regression (LR) is specifying the beneficial patterns in a regime. The multi-layer perceptron is a network of synaptic imitating the brain's neurons (7).

As a result, the neural network's input variable, Synaptic, will cause buried layers and eventual replies. Artificial neural network in contrast to other modeling methods such as regression better captures the nonlinearity and complexity of the changeable atmosphere of distinct construction projects.

The high degrees of uncertainty in the settlement prediction being better understood employing the artificial neural network, even to the higher levels of correctness. The artificial neural network (ANN) used to understand and resolve the problems of geotechnical engineering, like the prediction of bearing capacity of shallow footings and pile foundations and their settlement. The artificial neural network is progressively employed to model and optimize solutions to construction problems (8).

5. Types of neural networks

Neural networks are classified into many kinds according to algorithms used in the training processes and methods of communication such as feed-forward network, self-organizing map, and radial basis function networks. The most common types of ANN can be classified as follows:

A. *Multilayer perceptron (MLP)*

MLP is often used for regression and classification (8). This sort of design has more than three levels, with the inputs layer being the first and the outputs layer being the final. Between inputs and outputs, one or more hidden layers with the number of units considered during the design phase is stored in a layer. The number of units determined during the design phase was stored in one or more hidden layers between the inputs and outputs layers. Every node received input data, associated weights, and performed the function. The function that was chosen influenced network learning. After

that, the node used an activation function to generate output weights. The outputs layer algorithm worked on the hidden node and weights values, and the final value of outputs was determined (9).

B. *Feed Forward*

Feed forward is a unique MLP character. One or more layers are used to connect the dots. The Feed Forward network has been widely utilized to solve high-performance problems. If the problem is not stated, MLP requires hundreds of iterations to train, and then the general feed-forward for a network of equivalent size suffices (10). Feedforward was the most appropriate to develop predictive models for shallow foundations on gypseous soil soils. The best method for finding the optimum weight combination for feedforward neural networks is the back-propagation algorithm (11), based on first-order gradient descent. Feedforward networks trained with the back-propagation algorithm have already been applied successfully in many geotechnical engineering problems. A mixture of connection matrices is used to define the connectivity pattern for a multilayer feedforward network. Each level of connections between two immediately adjacent layers matrix of weights is used to describe it. For the multilayer that is totally connectedThe set of matrices for the feedforward network.

6. Statistical criteria

Performance evaluation is an interdisciplinary researc problem. Performance metrics (error measures) are vital components of the evaluation frameworks in various fields. In machine learning regression experiments, performance metrics compare the trained model predictions with the testing data set's actual (observed) data**.** The mean square error (MSE) and mean absolute error (MAE) are popular metrics used by models and estimators to compare anticipated and observed values (sample values). The RMS represents the (RMS) of the second sample moment of the disparities between observed and predicted

values, or the quadratic mean of these differences, (12).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_l)^2 \qquad (1)$$

where (O) and (P) are the forecast and objective magnitudes, in the entire no. of the trained or tested specimens.

In addition, equation of mean absolute error:

$$MAE = \frac{1}{n}\sum_{k=1}^{n} Oi - Ak \qquad (2)$$

4.1 Coefficient of Correlation (R)

The linear correlation between expected and observed values is defined as the coefficient of correlation, (the degree to which the expected and observed values match) (13)

$$R = \frac{\sum_{i=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2 (P_i - \bar{P})^2}} \qquad (3)$$

4.2 Coefficient of Efficiency (CE)

The following law can be used to compute the efficiency coefficient:

$$CE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \qquad (4)$$

4.3 Variance Account for (VAF)

There is also an extra equation called the (variance account for (VAF)) that may be used

to verify the performance of ANN's model (14).

5. Result and discussion

Results for predicting the surface settlement of the shallow foundation on a gypseous soil using the Artificial Neural Network (ANN) model is illustrated in figure 3 at 20%, 30%, 70%, and 80% testing consecutively. The effectiveness factor (R^2) as depicted in figure 2 was 0.76, 0.803, 0.741, and 0.751 respectively. The effectiveness factor approach 3 indicating a perfect correlation and a significant performance for the predicting model. However, the effectiveness factors for predicting the surface settlement using ANN model showed a lower value than one. Table 1 shows the results of the performance indices as the mean absolute error (MAE) and the mean square error (MSE) from 20% testing up to 80% and table 2 the model consists 100 neurons and model effectiveness indicators. MAE was increased with the testing increment. The highest MAE was recorded at 80% testing which was 0.733. The highest MSE was recorded at 70% testing which was 0.806. Therefore, this model exhibits good performance in term of settlement prediction and showes a low correlation between the measured and predicted settlement.

(a)

(b)

(c)   **(d)**
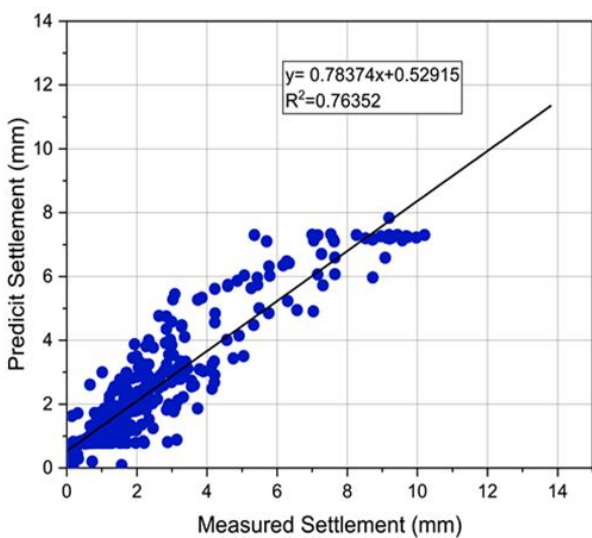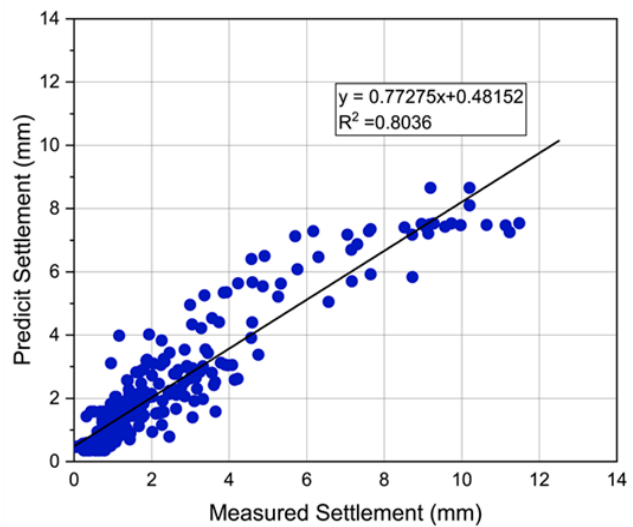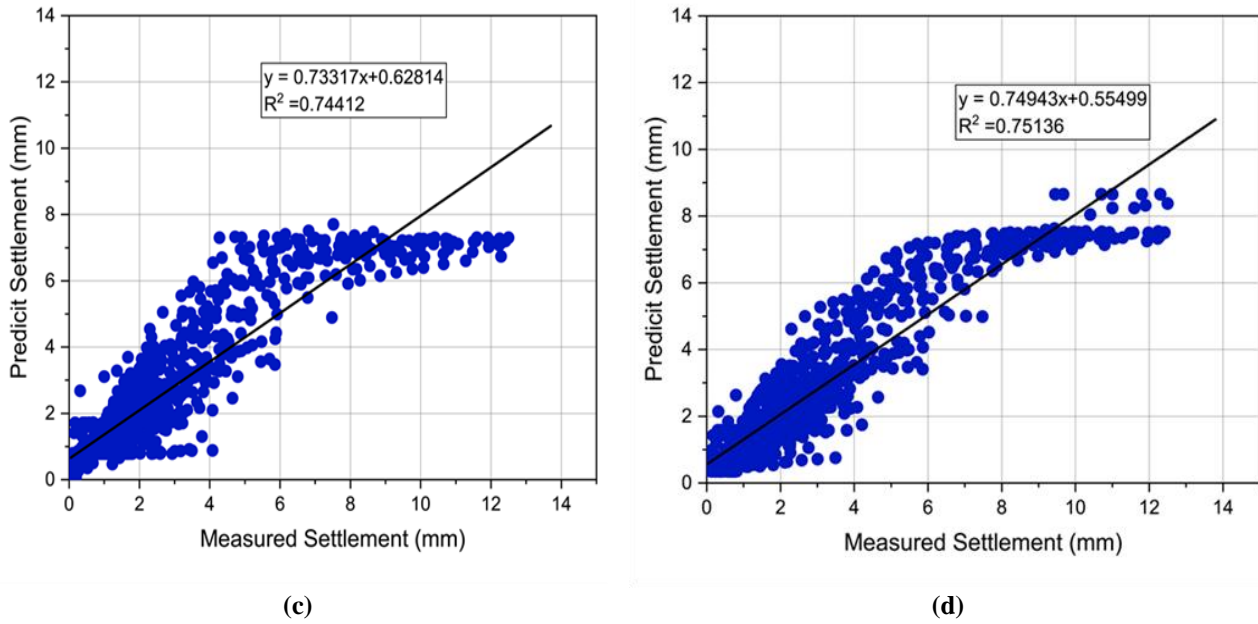
Figure 2. The measure and predicted settlement using ANN model: (a) the testing 20%, (b) the testing 30%, (c) the training 70%, and (d) the training 80%

Table 1: The performance indices of the ANN model

Data set	R^2	MSE	MAE	CE	VAF
30%	0.803	0.389	0.687	0.750	4.902
70%	0.744	0.806	0.746	0.742	5.207
20%	0.763	0.128	0.648	0.802	4.252
80%	0.751	0.710	0.751	0.751	5.146

Table 2: The ANN model performance for various neurons

No of neurons	Train 70%			Test 30%		
	R^2	MSE	MAE	R^2	MSE	MAE
10	0.677	1.807	1.986	0.773	0.902	1.452
20	0.685	1.694	1.894	0.775	0.880	1.384
30	0.717	1.490	1.628	0.778	0.735	1.274
40	0.738	1.287	1.379	0.781	0.694	0.936
50	0.739	1.037	1.285	0.784	0.575	0.892
60	0.739	0.984	0.979	0.800	0.483	0.835
70	0.744	0.958	0.874	0.800	0.461	0.775
80	0.744	0.885	0.796	0.801	0.438	0.739
90	0.744	0.846	0.769	0.801	0.399	0.695
100	0.744	0.806	0.746	0.803	0.389	0.687

Figure 3 depicts the model's ability to predict every measured value of the tested specimens during the testing phase. As can be shown, the model can accurately predict the majority of the specimens studied. Nonetheless, the artificial neural network model's effectiveness is almost immediately apparent during the testing phase.
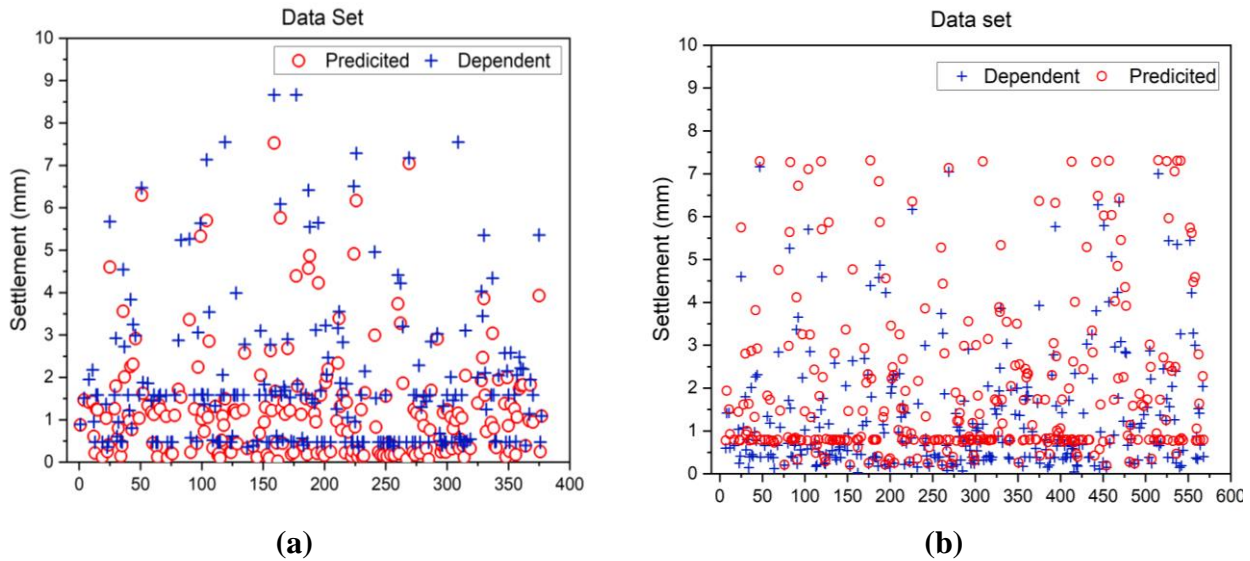
Figure 3. Comparison between dependent data and predicted data :(a) the testing 20% and (b) the testing 30%

The Figure 4 shows the accuracy of the prediction with the residual error of settlement ratio model, it can be concluded from that Figures that the majority of the predicted values are in a good agreement with the measured values.
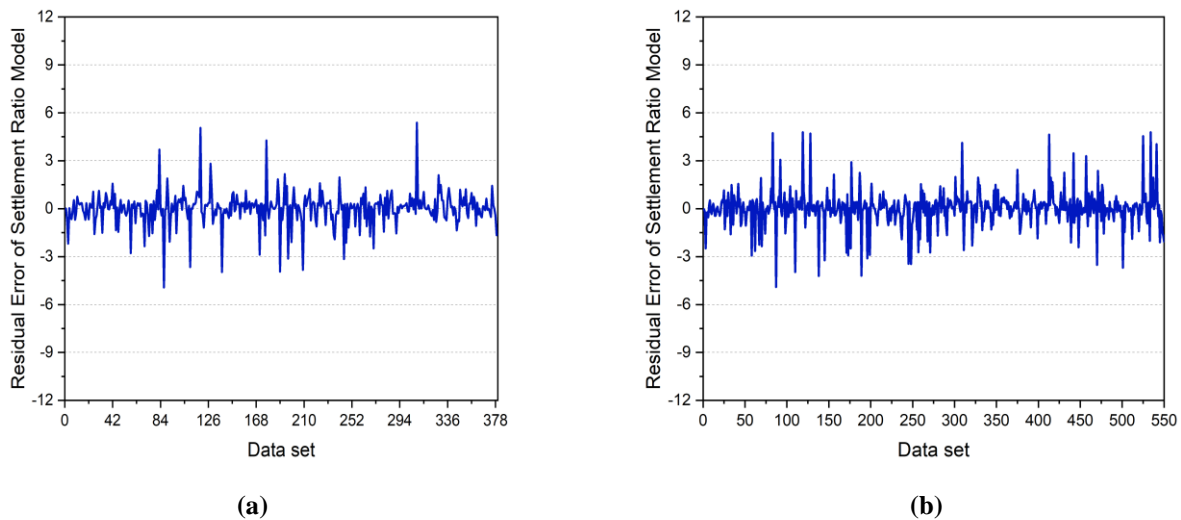

Figure 4. Residual error of settlement ratio ANN model: (a) the testing 20% and (b) the testing 30 %

6. Conclusions

1. This study has investigated the feasibility of using the artificial neural network (ANN) for predicting the settlement of the shallow foundation on a gypseous soil. ANN models were found to outperform the most commonly used traditional methods.
2. Artificial neural network (ANN) has the ability to predict the settlement of shallow footings on gypseous soil with a high degree of accuracy.

ANN model showed a fair performance. The performance indices as MAE and MSE showed high degree of uncertainty which were 0.733 and 0.806 respectively. The coefficient of efficiency and variance account were around 0.7 and 5 respectively.

References

[1] A. KI, "Effect of gypsum on the hydro-mechanical characteristics of partially saturated sandy soil " Ph.D. thesis, Geoenvironmental Research Centre, Cardiff School of Engineering, UK, Cardiff University, 2019.

[2] A. Ahmed and K. Ugai, "Environmental effects on durability of soil stabilized with recycled gypsum," *Cold regions science and technology,* vol. 66, no. 2-3, pp. 84-92, 2011.

[3] B. J. Nareeman, "A study on the scale effect on bearing capacity and settlement of shallow foundations," *International Journal of Engineering and Technology,* vol. 2, no. 3, pp. 480-488, 2012.

[4] B. Tarawneh, T. Masada, and S. Sargand, "Estimated and measured settlements of shallow foundation supporting bridge substructure," *Jordan Journal of Civil Engineering,* vol. 7, no. 2, pp. 224-235, 2013.

[5] H. MolaAbasi, M. Saberian, A. Khajeh, J. Li, and R. J. Chenari, "Settlement predictions of shallow foundations for non-cohesive soils based on CPT records-polynomial model," *Computers and Geotechnics,* vol. 128, p. 103811, 2020.

[6] A. J. Maren, C. T. Harston, and R. M. Pap, *Handbook of neural computing applications*. Academic Press, 2014.

[7] W. Zhang and A. T. Goh, "Multivariate adaptive regression splines and neural network models for prediction of pile drivability," *Geoscience Frontiers,* vol. 7, no. 1, pp. 45-52, 2016.

[8] W. Zhang and A. T. C. Goh, "Reliability analysis of geotechnical infrastructures," *Geoscience Frontiers,* vol. 9, p. 1595e1596, 2018.

[9] W. Zhang, R. Zhang, W. Wang, F. Zhang, and A. T. C. Goh, "A multivariate adaptive regression splines model for determining horizontal wall deflection envelope for braced excavations in clays," *Tunnelling and Underground Space Technology,* vol. 84, pp. 461-471, 2019.

[10] A. T. Goh, W. Zhang, and K. Wong, "Deterministic and reliability analysis of basal heave stability for excavation in spatial variable soils," *Computers and Geotechnics,* vol. 108, pp. 152-160, 2019.

[11] W. Zhang *et al.*, "State-of-the-art review of soft computing applications in underground excavations," *Geoscience Frontiers,* vol. 11, no. 4, pp. 1095-1106, 2020.

[12] R. B. Kaunda, R. B. Chase, A. E. Kehew, K. Kaugars, and J. P. Selegean, "Neural network modeling applications in active slope stability problems," *Environmental Earth Sciences,* vol. 60, no. 7, pp. 1545-1558, 2010.

[13] Y. Yukselen and Y. Erzin, "Artificial neural networks approach for zeta potential of Montmorillonite in the presence of different cations," *Environmental Geology,* vol. 54, no. 5, pp. 1059-1066, 2008.

[14] A. Ardakani and A. Kordnaeij, "Soil compaction parameters prediction using GMDH-type neural network and genetic algorithm," *European Journal of Environmental and Civil Engineering,* vol. 23, no. 4, pp. 449-462, 2019.

[15] Dawood, "strength stiffness and compressibility of understanding gypseous soil during wetting and soaking," civil, University of Technology, University of Technology, 2016.

[16] Q. A. Mehdi, "The Effect of Sand Particles Size on Bearing Capacity Factors of Shallow Footings ", civil, University of Technology, University of Technology, 2005.

[17] R. Salman, "Bearing capacity of shallow footing on compacted filling dune sand over reinforced gypseous soil," *Journal of Engineering,* vol. 19, no. 5, pp. 532-542, 2013.