

# Application of Artificial Neural Networking Technique to Predict the Geotechnical Aspects of Expansive Soil: A Review

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**Abstract:** Soil mechanics problems deal with various types of soil that exhibit erratic behaviour in the real world, one such soil being the expansive soil where it takes a lot of laboratory test procedures to ascertain the physical properties of this soil. Modeling the behaviour of the expansive soil is complex and sometimes beyond the aptitude of most traditional procedures of physically-based engineering approaches. Artificial neural networks (ANN) are the ones used for predicting the complex nature of the soil since it has shown superior predictive potential as compared to the conventional approaches. This review aims to deliver and discuss the numerous applications of artificial neural network technique accomplished by various researchers in the field of geotechnical engineering to predict several properties of the expansive soil such as free swell index, unconfined compressive strength, shear strength of the soil, swelling pressure and swell percent, compaction characteristics, and plasticity index. This paper will assist practising engineers in determining the best modelling approaches and formulating the necessary data for using the ANN technique to solve soil mechanics problems.

**Index Terms:** Artificial neural networks, Expansive soils, Free swell index and Swelling pressure.

## 1. Introduction

Expansive soils are well known for their peculiar behaviour during seasonal variations causing problems all over the world. It is well understood that larger stresses can be generated when a material's volume change is obstructed. When volume changes are permitted, the value of these stresses can rapidly decrease. Expansive soils cause damages to all manmade structures regardless of the materials used for the construction activity. Thus it is obvious to study the properties and effects of these soils when they are subjected to external loads and variation in moisture content. Laboratory experiments are a traditional manner of finding these parameters, which is cumbersome and time-consuming hence this result in using artificial neural network technique to counteract the issues. This review article demonstrates the various applications of the artificial neural network method employed in obtaining the geotechnical properties of expansive soil.

### 1.1 Artificial Neural Network

Artificial neural network (ANN) is a process of profound learning algorithms that had developed and progressed from the knowledge of biotic neural networks of humanoid brains. Here an effort is made to mimic the function of the human brain. Though artificial neural networks are called artificial intelligence, they can only be used with numeric data and structured data as input. They possess certain hindrances to accept the data in the form of image, text, and speech. A single-layer neural network is termed a perceptron but the artificial neural networks comprise multiple layers called multilayer perceptron (MLP). MLP's are the one which may have one or additional neurons or units and those units are linked with every other unit. Activation functions are used for each layer to establish non-linearity in the data. Some of the activation functions are Logistic or Sigmoid, Tanh, ReLU, and Leaky ReLU function. ANN broadly consists of two

segments namely, forward propagation and backward propagation. In the forward propagation, the input data are propagated forward considering increasing weights, the addition of bias, and applying activation function. However, backward propagation is considered as the most vital phase which encompasses the determination of ideal parameters for the proposed model by propagating the neural network layer towards backward direction thus the backward propagation necessitates an optimum function to the ideal weights for the model. Regression and cataloging tasks can also be performed using ANN but the output layers require variation in the activation functions.

The ANNs architecture comprises a sequence of processing elements or nodes [1]. These are organized in a layer namely, an input layer and an output layer with the hidden layer being one or more as shown in Figure 1. From the previous layer ( $X_i$ ), the input layer from every processing element is multiplied with an adjustable link weight ( $W_{ji}$ ). At each processing element,  $W_{ji}X_i$  is summed with a threshold value  $\theta_j$  is added. This input  $I_j$  is forwarded through an indiscriminate transfer function  $f(\cdot)$  to generate the output of the processing elements  $Y_j$ . The output of single processing element delivers the input to the processing elements in the subsequent layer. This procedure is highlighted in Eqs. (1) and (2), and shown in Figure 1.

$$I_j = \sum W_{ji} X_i + \theta_j \quad (1)$$

$$Y_j = f(I_j) \quad (2)$$

Input parameters are the first phase in the propagation of the data in the ANN. The network gets adjusted based on the training data set and uses a knowledge rule in producing the smallest possible error that is obtained from input/output mapping and this is termed as training. After the training process, the model is further assessed on its performance using an independent validation set [1].

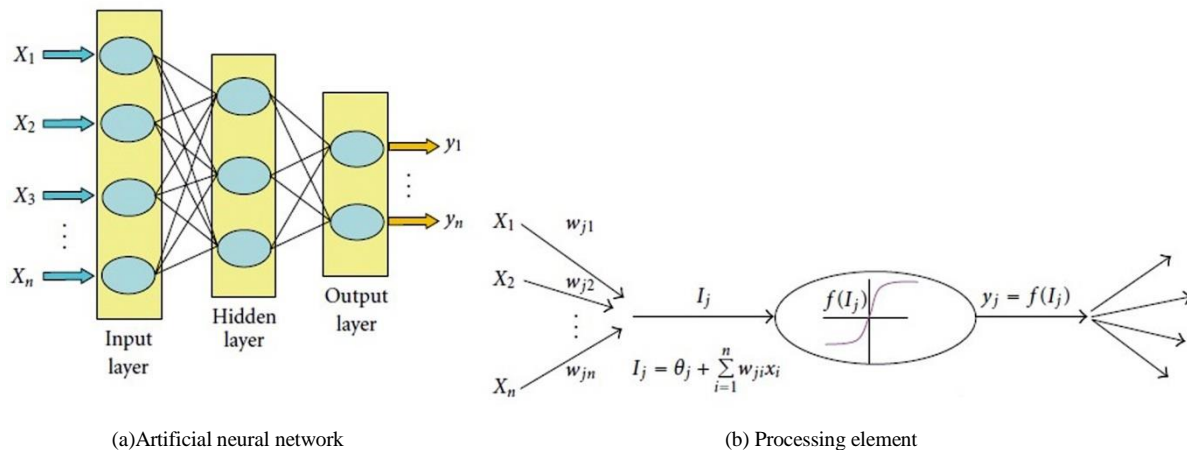


Fig.1. Structural operation of artificial neural networks [1]

Some of the advantages of using ANN techniques are; Information is stored across the whole network, ability to operate with a limited amount of information, tolerance for flaws, having a distributed memory system is advantageous, gradual deterioration, machine learning capabilities, and has the capacity to process data in parallel. They also possess some of the disadvantages such as; hardware is required, the network's behaviour is unexplained, choosing the right network structure, difficulty in communicating the issue to the network, and the network's duration is unclear.

## 1.2 Objectives of the Review

The following are the objectives of the review paper and the work presents the current level of knowledge on the subject in general.

- To present the various applications of the ANN tool in predicting black cotton soil properties.
- To understand the modelling procedures using ANN considering the input and output variables of the soil.

## 2. Related Work

Numerous studies have been carried out to predict the properties of the expansive soil. This section provides insight into the several research papers along with the methodology and results. The sub-clauses here will throw lights on the different physical properties of the expansive soil such as free swell index, unconfined compressive strength, cohesion and angle of internal friction of the soil, Swelling pressure and swell percent, plasticity index, optimum moisture content and maximum dry density.

### 2.1 Free swell index

Dutta et.al [2] utilized artificial neural networks to predict free swell index for expansive soil. Plasticity index and shrinkage index are considered as input factors for the ANN model, while the output parameter is a free swell index. A back propagation model with 2-2-1 architecture is used in this study for the ANN model. The work also takes care of performance measures used to recognize the efficacy of the developed neural network model, they are the coefficient of correlations ( $r$ ), coefficient of determination ( $R^2$ ), mean squared error (MSE), relative mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE). A multiple regression model is also carried out using Data fit software and the equation is generated. Results have revealed that the coefficient of correlations and coefficient of determination of the regression model is less compared to the one generated from the neural network model. Further, it has been concluded that the efficacy of the ANN model is superior to the one generated from regression modeling. The equation obtained from multiple regression analysis had incapability in the prediction of the free swell potential of the expansive soil. Sensitivity analysis is performed to understand the influence of plasticity index and shrinkage index as input parameters to the free swell index as output parameter and results exposed that plasticity index of 63.97% followed by 36.03% of shrinkage index is affecting free swell index. The results of the study conclude that the projected neural network architecture is capable to predict nearby to the definite free swell index of the soil.

### 2.2 Unconfined compressive strength

Sathyapriya et.al [3] carried out a study on the prediction of unconfined compressive strength (UCS) of a treated expansive clay soil by artificial neural networks and regression analysis. Here authors have used various variables in developing a model, they are the curing period of the soil sample, bottom ash, and eco sand dosages as stabilizers, liquid limit (LL), plasticity index (IP), and free swell index. The regression analysis was performed over three samples namely soil stabilized with varying percentage of bottom ash (RA-1), soil stabilized with varying percentage of eco sand (RA-2), and blend of bottom ash with eco sand (RA-3). The regression equations have been obtained for all three samples and the results for the UCS revealed that  $R^2$  as 0.919, 0.931, and 0.946 for samples RA-1, RA-2, and RA-3. Researchers have used a feed-forward back propagation algorithm with 13 numbers of neurons with one hidden layer and mean square error is used for performance measures. Coefficient of correlations ( $r$ ) and coefficient of determination ( $R^2$ ) for three samples on UCS values are studied and obtained  $R^2$  as 0.911, 0.986, and 0.996 for NN-1, NN-2, and NN-3 where NN corresponds to neural networks model. The outcome of the work exhibited that the prediction using the ANN tool highlighted an enhanced fit than one going for regression analysis between UCS and its relative parameters.

### 2.3 Cohesion and angle of internal friction of the soil (shear strength parameters)

Jain et.al [4] has made a research contribution on the prediction of soil shear strength of medium compressibility soil. It is observed that the basic properties of the soil are responsible to make an impact on the soil shear strength in unconsolidated undrained conditions. The work is carried forward by using the back propagation algorithm. A triaxial shear experimental setup has been used to perform an unconsolidated undrained test and the necessary data for developing a model are generated. A total of 198 assessment results are made available from the test setup, out of which 120 are allocated to train the model, and the rest of the data are used equally for validation and testing purposes. An architecture called radial bases function network (RBN) is used in the work comprising three input parameters such as compaction energy, degree of saturation, and dry density. The architecture has one hidden layer with 42 numbers of optimum neurons and the output nodes being the cohesion of the soil ( $c$ ) and angle of friction ( $\phi$ ) of the soil. In the multilayer perceptron network (MLPN), the architecture of 5-35-30-40-02 was trained and the results are compared with the experimental results. The results of cohesion and angle of friction predicted from MLPN are closer to the experimental results than the RBN model. In MLPN, the mean square error was 0.0642 and 0.253 in the RBN model which concludes that the attempted MLPN model with back propagation is more appropriate than RBN hence the MLPN model suits for prediction of shear strength of the soil.

### 2.4 Swelling pressure and swell percent

Ikizler et.al [5] conducted research work to estimate the swelling pressures of expansive soils by artificial neural networks. The artificial neural network (ANN) approach was used to develop a model having two types of transmitted pressures such as horizontal swelling pressure and perpendicular swelling pressure. The lateral and vertical pressures were measured with varying thicknesses of expanded polystyrene geofoam (EPS) located in between the steel test box and expansive soil. Time and thickness of geofoam are used as input variables and output being lateral and vertical swelling pressures of the soil. Later, ANN was trained to make use of these pressures to predict transferred lateral and vertical swelling pressures. Multi-linear regression (MLR) is a technique used in the present study to predict some anonymous variables. Multilayer perceptron (MLP) architecture was used with one hidden layer and for the adjustment of weights a training algorithm called Levenberg-Marquardt (LM) is used. An activation function called logarithmic sigmoid was used for hidden and output layers. A simple trial and error technique was used to discover the numeral of hidden layer neurons. The statistics such as the root mean square errors (RMSE), the determination coefficient ( $R^2$ ), and

relative absolute error (RAE) were used in the work. Based on the results, the RAE statistics of the ANN models are 0.038 and 0.057 for lateral and vertical swelling pressures. An ANN 2-6-1 model bears 2 input, 6 hidden and 1 output layer neurons that have produced the lowest RMSE of 0.354 and highest  $R^2$  of 0.999 among all iteration values for lateral swelling pressure. However, the same model generates the lowest RMSE of 0.813 and highest  $R^2$  of 0.997 towards vertical swelling pressure. Therefore an ANN 2-6-1 model looked more reliable and optimal topology for both swelling pressures. As projected by the authors, the relationship between measured swelling pressures with predicted ones for testing in ANN as well as in MLR is linear. MLR estimates  $R^2$  of 0.562 with RMSE of 42.67 and RAE of 0.756 for lateral swelling pressure but for vertical swelling pressure,  $R^2$  is 0.869 with an RMSE of 28.50 and RAE of 0.349. The outcome of the study exposed that the prediction made by the ANN technique gives good results than that estimated using MLR.

Merouane et.al [6] examined swelling factors of two different clayey soils procured from Algeria by artificial neural networks (ANN). The entire work comprises of two parts, in the first part the researchers have made their insight towards the identification and classification of swelling perspective of two clays and then a multiple linear regression analysis (MLR) is carried out to quantify the reliability of the observations such as pressure and swelling potential. In the second part, the work progresses on a prediction method for pressure and swelling amplitude using ANN. Experimental test data are utilized to develop a model and enactment indices namely, coefficient of determination ( $R^2$ ), and the mean squared error was deliberate to check the prediction capability and precision of the developed ANNs models. Statistical analysis includes all geotechnical variables such as the depth of the soil, the clay content, the natural water content, the liquid limit, the plasticity index, the activity, the dry density, the swelling pressure, and the swelling amplitude. This statistical study revealed the coefficient of variation of 60.61% and 70.78% for pressure and swelling amplitude. MLR was performed for two models on both swelling pressure and amplitude which obtained the results corresponding to the swelling pressure of 41.81% for  $R^2$  value under model-1 and 52.46% for  $R^2$  value under model-2. Similarly, 58.04% for  $R^2$  value under model-1 and 57.78 % for  $R^2$  value under model-2 were noted conforming to swelling amplitude. However, two models were developed under the ANN technique, one to predict swelling pressure and the other to predict swelling amplitude. The input parameters comprise of seven variables such as the clay content, the natural water content, the depth of the soil, the plasticity index, the activity, the liquid limit, and the dry density. Eight and three hidden layers were considered for model-1 and model-2 respectively. The output parameters are swelling amplitude and pressure. A total of 90 data sets were available for swelling pressure and 65 data sets for the swelling amplitude. For training purposes, 70% of the data are used while 30% of the data is allocated for validation and testing. It is observed that for swelling pressure, the model-1 generates a correlation coefficient (R) of 0.96 and holds 4.79 as mean square error (MSE) however, these outcomes changes to 0.95 as R and 0.018 as MSE for swelling amplitude. Based on the validation test data, it is possible to conclude that there is a fair amount of accuracy for both the models for both output parameters.

Erzin and Gunes [7] conceded a work on the prediction technique using neural networks to understand swell percent and swell pressure of expansive soil. As said, here artificial neural networks (ANN) and multiple regression analysis (MRA) models are developed to estimate swell pressure and swell percent. Results used for models are obtained from laboratory free swell test considering variable soil properties. Two models under each category are used, ANN-1 and ANN-2 under artificial neural network and MRA-1 and MRA-2 under multiple regression analysis. ANN-1 and MRA-1 are explicitly used for the prediction of swell percent whereas ANN-2 and MRA-2 are intended for the prediction of swell pressure. In together with the developed model, the work also highlights some of the performance indices such as determination coefficient ( $R^2$ ), mean absolute error (MAE), root mean square error (RMSE), and variance account (VAF) was used to authenticate the ANN and MRA models. At the training phase of the model, an algorithm named Levenberg-Marquardt back propagation is used. The input parameters such as clay percent, cation exchange capacity, plasticity index, dry unit weight, and water content are selected meanwhile the output parameter being the swell content of the soil sample in the ANN-1 model. It had used 56% of data for training, 20%, and 24% for validation and testing. Based on the analysis results, the optimal performance of the ANN-1 model seems to have eight neurons in the hidden layer with 14 epochs and a 0.001 momentum factor. An ANN-2 model is designated to have six inputs and one output that is a swell pressure and here the six inputs used are clay percent, cation exchange capacity, plasticity index, dry unit weight, water content and swell percent. Based on the analysis results, the optimal performance of the ANN-2 model seems to have two and eight neurons in the hidden layer with 16 epochs and a 0.001 momentum factor. The MRA-1 and MRA-2 had reflected the determination coefficient of 0.95 and 0.67. The results states that both ANN models have ensued in higher performance when related to MRA models also the performance level in the neural network had exhibited that the model can be used to minimize the uncertainties met during dealing with soil mechanics problems.

## 2.5 Plasticity index, optimum moisture content and maximum dry density

Bahmed et.al [8] have conducted research work on using the ANN tool to forecast some geotechnical properties of clayey soils with lime as a stabilizing agent. The objective of the work was to predict plasticity index (PI), maximum dry density (MDD), and optimum moisture content (OMC) using three models namely plasticity index model (PI-ANN model) maximum dry density model (MDD-ANN model), and optimum moisture content model (OMC-ANN model).



A total of 80 and 27 types of soil are considered as a database for the ANNs model by referring to the research projects carried out worldwide and published. This comprises 280 values of plasticity index and 122 values of MDD and OMC. Model development consists of a back propagation network with an algorithm called Levenberg-Marquardt uses a feed-forward architecture. The PI-ANN model corresponds to have seven neurons with one hidden layer where the regression values of all data set were equal to 0.91. The MDD-ANN model constituted with eleven neurons and one hidden layer architecture and in this model, Atterberg limits and lime content are chosen as an input variable to generate MDD as an output. The regression values of altogether registers for the MDD-ANN exemplary were projected as 0.83. But in the OMC-ANN model, consists of nine neurons with one hidden layer however, the model was established considering the effect of both Atterberg limits and lime content and the regression results being 0.83 for all data sets. It is observed that the validation is adopted for all three models. Firstly, the PI-ANN model was developed with a large number of records for a variety of soil and obtained a correlation coefficient of 0.94 with an average error of 9.16% between the experimental and predicted results. Secondly, the MDD-ANN model was developed by a total of eight hidden records and attained a correlation coefficient of 0.94 with an average error of 0.86% between the experimental and predicted outcomes. Lastly, the OMC-ANN model was developed by a total of nine hidden records and attained a correlation coefficient of 0.94 with an average error of 4.17% between the experimental and predicted outcomes. Study indicates that the developed ANN models can be meritoriously used in the case of quick prediction of plasticity index, maximum dry density, and optimum moisture content properties of treated clayey soils.

Salahudeen et.al [9] have used artificial neural network techniques to predict compaction characteristics of expansive soil treated with cement kiln dust. Three compaction energies were used at the laboratory to regulate the properties of natural soil and cement kiln dust-treated soil. The effort is targeted to cultivate an optimal neural network using soil properties for the optimum moisture content (OMC) and maximum dry density (MDD) of the natural expansive soil and the soil treated with cement kiln dust. Multilayer perceptron (MLP) by feed-forward back propagation algorithm is used. The ANN model had ten input parameters and two output parameters, the input parameters being linear shrinkage, the specific gravity free swell index, the effective particle size of the soil ( $D_{10}$ ,  $D_{30}$ , and  $D_{60}$ ), coefficient of gradation, uniformity coefficient, liquid limit, and plastic limit. The output targets are OMC and MDD of the soil. For model training, 70% of the data sets were made available while 15% each was used for testing and validation purposes. Performance evaluation of the model has been made by the statistical measures such as correlation coefficient (R), mean absolute error (MAE) and the root mean square error (RMSE). From the statistical results, the model had performed acceptably with high correlation coefficient values and low MAE values. The best networks such as NN 10-5-1 and NN 10-7-1 were selected for training in ANN towards OMC and MDD prediction. The network performed well and generated the correlation coefficient values of 0.983 for OMC and 0.988 for MDD respectively. Result of the work exhibited that there is a robust correlation between the experimental test data and the prediction made through the ANN technique.

### 3. Conclusions

An extensive study was undertaken on the uses of the artificial neural network approach on expansive soil, using the work of certain researchers as a reference. Geotechnical engineering is prone to encountering challenges that are both difficult and poorly known. Artificial neural network (ANN) has many benefits over more conventional computational approaches in this respect. ANN techniques are the data-oriented methods in which the developed models are enriched based on the training of input-output data sets to regulate the structure and factors of the model. It was evident from the study, that the ANN technique can be adopted for the determination of physical properties of the expansive soil such as free swell index, unconfined compressive strength, shear strength of the soil, swelling pressure, swell percent, compaction characteristics, and plasticity index. It is also observed that ANN techniques perform better than the traditional methods substantially reducing time and efforts also this method shall work as a complement to conventional testing procedures.

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