Plasticity prediction of expansive soil treated with sand by artificial neural network

Salima AMRI (saliamri@yahoo.fr)
Yahia Fares University
Abdelkrim BENNABI
Université Paris-Est, Institut de Recherche en Constructibilité, Ecole Spéciale des Travaux Publics
Rabah HAMZAOUI
Université Paris-Est, Institut de Recherche en Constructibilité, Ecole Spéciale des Travaux Publics
Mustapha AKCHICHE
University of Science and Technology Houari Boumediene
Mahmoud SERRAYE
Blida1 University

Research Article

Keywords: Clay, sand, plasticity, treatment, artificial neural network, prediction.

Posted Date: April 26th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1582312/v1

Abstract

Clay soils consist of fine particles and are generally characterized by low strength. The interactions between clays and water result in high-plasticity clay mixtures that can easily deform or crack. It should be noted that the addition of sand to expansive soils can help to improve their particle size and reduce their plasticity, and consequently augment their strength. The present study aims mainly to develop a model for the prediction of the plasticity index (PI) of soil treated with sand, at various contents using the artificial neural network (ANN) method. It was revealed that the ANN technique ensures good prediction accuracy for a large number of parameters related to geotechnical problems. For the purpose of predicting the plasticity index values of sand-treated soils, the results of experimental tests that were conducted on 38 soil samples were collected and thoroughly analyzed. It was decided to consider three inputs, namely the plastic limit, liquid limit, and sand percentage, while there was only one output, i.e. the plasticity index. The results of the analyses conducted in this study indicated that the artificial neural network (ANN) model might be quite efficient in predicting the plasticity index of soils treated with sand. Afterwards, an experimental investigation was carried out on the clayey soil that was brought from the Wilaya (Province) of Medea in Algeria. This soil was treated with dune sand at different percentages, and the results obtained were compared with those predicted by the artificial neural network (ANN) technique.

1. Introduction

Problems with clayey soils are frequently encountered in civil engineering constructions. They can be found either in natural grounds (foundations, slopes, retaining walls, excavations), or in compacted soils for the construction of earthworks (embankments, dikes, dams), or in backfilling trenches and walls. This type of soils is mainly characterized with poor bearing capacity and low strength. It should be known that various treatment techniques can be utilized to improve the performance of clayey soils. This can indeed be done by adding an inert material, such as sand in proportions to be determined, before proceeding with the compaction of the mixture. This approach allows enhancing the physical and mechanical properties of any clay soil (Louafi and Bahar, 2012 ; Prasad and Sharma, 2014 ; Cabalar and Mustafa, 2015 ; Nagaraj, 2016 ; Amri et al., 2019 ; Alkroosh et al., 2021; Phanikumar et al., 2021). It is noteworthy to mention that the plasticity index (PI) of soils is generally viewed as an important criterion in the field of geotechnical engineering. It is a parameter that is generally used to identify and classify clayey soils. It is noteworthy that soil plasticity depends on various factors, such as the amount of fines present in the mixture, the nature of soil and the amount of water it contains.

In this context, a large number of studies available in the broader literature have examined the effect of adding sand to clay soils for the purpose of improving their plasticity index, and consequently to change the plasticity of soil from medium to low, in accordance with the unified soil classification system (USCS). In this context, authors Ma et al. (2018) investigated the effect of adding sand at various percentages, i.e. 0%, 8%, 16% and 24%, to expansive soil from China. They found out that the plasticity index of that sand-treated soil was significantly improved. Similarly, researchers Atemimi et al. (2021) reported a series of consistency limits of clayey soils treated with different contents of sand (0%, 10%, 15%, and 20%). They also found out that the addition of sand to a clayey soil allows enhancing its plasticity index. In addition, the liquid limit and plastic limit of the studied clayey soil were measured in accordance with the standard method. They were found respectively equal to 81% and 42%. However, when mixed with 20% of sand, they dropped to 35 % and 27 %, respectively. In this regard, Goufi et al. (2022) examined the behavior of clay soil through its partial replacement (10, 20 and 30 %) with dune sand. They found out that the liquid limit, plastic limit and plasticity index decreased as the dune sand content augmented. It should be mentioned that the plasticity index (PI) dropped from 51.9% for untreated clay to 33.8 % for soil incorporating 30% of dune sand. Consequently, it was deemed necessary to design and develop techniques that can help to predict the plasticity index of soils using the ANN method that is mainly viewed as a general prediction tool which is widely used in various fields in civil engineering (Kaveh and Khalegi, 2000 ; Yang and Rosenbaum ,2002 ; Zhou et al., 2016 ; Amiri and Hatami,2022 ; Eyo et al .,2022). It is noteworthy to mention that several researchers have been using the ANN method for the prediction of the plasticity index of various types of clayey soils. In this context, Taleb Bahmed et al. (2017) applied the ANN technique for the purpose of assessing the plasticity index of clay soil stabilized with lime. A total of 280 plasticity index values were collected from various data sets recorded by a number of researchers from the literature. These values were utilized in the ANN method which turned out to be a quite efficient approach in predicting the plasticity index of sand-treated clayey soil stabilized with lime. With regard to Sari Ahmed et al. (2018), they carried out a study in order to examine the affect of fly ash on the behavior of high-plasticity clay soils using the ANN method. For this, 29 fly ash -stabilized soils were utilized for developing models intended to predict the consistency limits. The liquid limit and the amount of fly ash to be used were taken as input factors and the plasticity index as output parameter. These researchers revealed that the ANN technique is highly efficient in predicting the plasticity index (PI) of clay soils stabilized with fly ash. In this context, Jasim et al. (2019) applied the ANN technique to predict the plasticity index of soils in Baghdad, the capital city of Iraq, and also used an experimental database. As for Akbay Arama et al. (2021), they developed and implemented models based on the ANN method for predicting the plasticity index of very highly plastic clayey soils. In addition, some empirical relationships were employed to evaluate the plastic limit and plasticity index from the liquid limit. It is worth emphasizing that the data used in the models were obtained from experimental consistency tests that were carried out on various clay soils from the city of Istanbul, in Turkey. The results obtained indicated that adopting artificial neural network (ANN) models can lead to better results than those obtained with the regression expressions.

In the context of this study, the ANN technique can efficiently be used to evaluate the plasticity index of clay soil treated with sand Therefore, it can be asserted that the prediction of the plasticity index was successfully achieved with the ANN technique. Then, the results obtained were compared with those obtained from the experimental tests that were carried out on clay soil of Medea in Algeria treated with dune sand at different contents.

2. Artificial Neural Network Analysis

Artificial neural networks (ANN) are computing methods that are based on the functioning of the human brain neural network. They are mainly intended to analyze and process information. Over the last few years, this technique has acquired increasing importance in various engineering fields due to its high performance and its simplicity of conception and use. The ANN architecture consists of a series of simulated neurons ; each neuron corresponds to a node. These neurons are found in various layers, i.e. the input layer, the output layer, and one or more hidden layers. The architecture of the ANN model is illustrated in Fig. 1. According to this figure, this network has an input layer, one or more hidden layers, and an output layer. Each layer contains computational units (neurons) connected to other neurons by weights. Each neuron can in fact calculate a weighted sum of its inputs which is transmitted to a transfer function (*f*) in order to produce the outputs (Equations 1–2).

$$I_j = \varnothing_j + \sum_{i=1}^{n} W_{ji} \times X_i$$

1

$$Y_j = f\left(I_j\right)$$

2

Where

I_j : output value ; X_i : the input value ; W_{ji}: the weights of the connections ;$\varnothing_j$: the bias ; n : the number of inputs.

For each layer of the neural network in a multilayer perceptron (MLP) network, there is also a bias term. A bias is a neuron in which the activation function is always equal to 1. Several functions can be used for the activation of artificial neural networks. The most popular and commonly used ones are the sigmoid, binary step, hyperbolic tangent, and radial functions (Arama, 2021). Training an artificial neural network (ANN) is essential if one needs to achieve good performance. Consequently, the training of this network was carried out using several algorithms. It is worth indicating that the backpropagation algorithm is widely applied in this case. The training signal is transmitted from the output layer to the hidden layer, and then returns back to the output layer. This process is repeated iteratively until the desired error is reached (Goutham and Krishnaiah, 2021). Afterwards, the training phase of the model is validated and tested for an independent set of values. The artificial neural network (ANN) is the most commonly applied computational model in diverse areas of geotechnical engineering for solving various types of complex problems such as liquefaction, settling, swelling, strength, and bearing capacity.

2.1. Data construction

In this study, the results of the experimental tests that were conducted on 38 samples of sand-treated soil were collected for the purpose of developing an ANN model capable of predicting the plasticity index. It should be noted that these data were gathered from several research studies available in the literature. In addition, a total of 197 plasticity index values found in the literature were randomly divided into three categories : the first category was for training (70%), the second one for testing (15%), and the third one (15%) for the validation of the analysis model. All the data involved in this model are shown in Table 1, while the statistical data-collection parameters are presented in Table 2. The database obtained is clearly presented in the plasticity chart and is illustrated in Fig. 2. One may easily note that most data are under the A-line and U-line.

2.2. ANN model development

The ANN models depend on various parameters such as the associated topology (number of inputs, number of outputs, and number of hidden layers) ; they also depend on the learning parameters like the transfer function, the number of learning cycles, and the maximum error (Taleb Bahmed et al., 2017). In this study, the Matlab simulation program was employed to develop the ANN model using the back-propagation training algorithm. The minimal error was obtained by applying Eq. 3, while the mean relative error could be determined by means of Eq. 4 (Kellouche et al., 2021). It should be noted that the best performance was obtained when the structure of the ANN model included three layers : one input layer, one hidden layer, and one output layer. It is useful to recall that each layer consists of a number of neurons. In this case, there are three neurons in the input layer, three neurons in the hidden layer and one neuron in the output layer, as is illustrated in Fig. 3. Further, the input variables used were the liquid limit (%), plastic limit (%), and sand content (%), while the output parameter was the plasticity index (%).The normalization of the data between − 1 and + 1 before their introduction into the ANN models was done in order to make them compatible with the limits of the "tan-sigmoid" transfer function which was used in the hidden layer as well as in the output layer (Eq. 5).

$$E(\backslash\%) = ABS\left(\frac{O_{EXP} - O_{ANN}}{O_{EXP}}\right) \times 100$$

3

Where : O_{EXP} the experimental values ; O_{ANN} the predicted values.

MER(%) = $\frac{\sum_{i=1}^{N} E}{N}$ (4)

Where : N the number of specimen.

$f(\ \sigma) = \frac{1}{(1 + e^{-\sigma})}$ (5)

Where : f the activation function ; σ weighting function.

2.3. The performance of the ANN for predicting plasticity index

Figure 4 gives an explicit comparison between the sand-treated clay soils plasticity index values obtained with the ANN model and the experimental data used in the training and test sets. This same figure clearly indicates that the correlation coefficient R^2 (0.99) obtained is significantly high for the training sets, and it is a high (0.97) for the testing sets. The value $R^2 = 0.99$ is used for the validation of the model. The ANN model was validated using the four experimental results of Gokalp (2009), Jjuuko et al. (2011), Öncü and Bilsel (2018), and Jyothi et al. (2019) ; these results are not included in the training database. This was done for the purpose of predicting the plasticity index from the input parameters such as the liquid limit, plastic limit, and percentage of sand. Based on the results obtained (Table 3), it could be noted that the overall average error between the experimental results and the values predicted by the ANN model was equal to 2.48%. This small error value allowed concluding that the proposed model is quite accurate. This model can be used as a reliable tool for the prediction of plasticity index (PI) of clay soils treated with sand.

3. Experimental Procedure

3.1. Materials used

The very plastic clay, which is the subject of this study, comes from the region of Boughezoul. It was taken along the route of the road project linking Ksar El Boukhari to Boughezoul in the region of the Wilaya of Medea (Algeria). This locality is situated at about 160 Km to the south of Algiers. The soil under study was collected from under natural ground surface, at a depth of (0.5–1.5) m, as illustrated in Fig. 5. The dune sand used was retrieved from Zaafrane, a small town in the Wilaya of Djelfa, not far from the Wilaya of Médéa. This type of sand is widely used in the construction and public works. It was collected manually and placed in plastic bags. The geotechnical properties of the clay soil and dune sand were determined in accordance with Standard NF P. The recorded data are all summarized in Table (4). In addition, Figs. 6 and 7 present the mineralogical analysis for the clay soil and dune sand.

The clay soil was first examined, and was then classified as highly plastic (At) according to the Unified Soil Classification System (USCS) and to the Central Laboratory for Roads and Bridges (Laboratoire Central des Ponts et Chaussées - LCPC) as well.

The mineralogical analyses of the clayey soil and dune sand were carried out using the X-ray diffraction (XRD) technique. The results obtained show that the Boughezoul clayey soil consists of several minerals that essentially exhibit a hexagonal structure quartz (SiO_2) and calcite ($CaCO_3$), in addition to monoclinic gypsum, Montmorillonite (Bentonite), Kaolinite with triclinic structure, crystallized Monoclinic Illite, orthorhombic Illite- Montmorillonite and Kaolinite-Montmorillonite. On the other side, the mineralogical analysis of the clay from Boughezoul shows the presence of montmorillonite in different phases, which explains its high plasticity and significant swelling potential. Moreover, the X-ray diffraction analysis results of the dune sand showed the presence of a large amount of quartz (SiO_2) and calcite ($CaCO_3$) both showing a hexagonal structure, in addition to the orthorhombic silicon oxide and cubic calcium oxide. The dune sand used in this investigation can be considered as essentially siliceous in nature.

3.2. Consistency limits

The consistency limits or Atterberg limits are physical properties describing fine soils. They are generally used to identify and characterize fine soils ; they can also help in measuring the water content that characterizes the different soil states (plastic, semi-plastic, and liquid). It should also be noted that the approaches applied to obtain the consistency limits are those recommended by the French Standard (NF P 94 – 051) for soils with particle size less than 0.40 mm. With regard to the plasticity index value, it is defined as the difference between the liquid limit and the plastic limit. The plasticity index value is essentially used to classify soils. In the present study, a series of Atterberg limit tests were carried out for the purpose of assessing the behavior of the clayey soil from Boughezoul of the Wilaya Medea (Algeria) when mixed with various dune sand contents (0%, 10%, 20%, 30% and 40%) by dry weight.

3.3. The effect of adding dune sand on consistency limits

The results of the Atterberg limits test that was carried out on Boughezoul clayey soil to which dune sand was added at various proportions are reported in Table 5 and are illustrated in Fig. 8. These results show explicitly that the liquid limit (LL) and plastic limit (PL) values decrease as the dune sand content goes up. Indeed, it was found that the liquid limit and plastic limit values dropped, respectively, from 74.5 (%) to 45.7 (%) and from 33.66–22.6%, for dune sand rates varying from 0–40%. In addition, Fig. 8 shows that the plasticity index was enhanced as the proportion of dune sand augmented. Moreover, it was found that this plasticity index dropped from 40.84% for untreated clayey soil (free of sand) to 23.1% for clayey soil incorporating 40% of dune sand. It was also revealed that the decrease in the plasticity index value was primarily attributed to the decrease in the liquid limit and plastic limit values. Regarding Fig. 9, it presents the Casagrande plasticity chart which shows the impact of dune sand content on the classification of the clayey soil treated with 40% of dune sand. According to this plasticity chart, this clay soil went from high plasticity to low plasticity.

Furthermore, the decrease in the liquid limit and plastic limit values were essentially assigned to the reduction in clay particles in the mixtures (clay soil + sand), which in turn diminished the capacity of these mixtures to absorb water. This also led to the decline in the specific surface area of the mixtures and engendered the decrease in the cation exchange capacity due to the incorporation of sand particles into clay. It should also be mentioned that the same behavior has previously been reported by other researchers for clayey soils treated with sand. In this context, Kolay and Ramesh (2016) examined the behavior of kaolinite and bentonite clays treated with different sand contents (0%, 10%, 20%, 30%, 40% and 50%). They found out that these types of clay have liquid limit and plastic limit values respectively equal to 75.84% and 28.49%. Then, with the addition of 50% of sand, these values decreased significantly to 32.05% and 15.42%, respectively. In addition, for bentonite clay, these authors found out that the liquid limit dropped from 603.07–120.80%, and the plastic limit from 94.51–65.85%, with addition of 50% of sand. With regard to Harichane et al. (2017), they investigated the effect of dune sand on the Atterberg limits of clay soil brought from the Wilaya of Chlef in Algeria. Indeed, it was found that the addition of 20% of dune sand caused the liquid limits and plastic limits to decrease respectively from 78.42–62.41%

and from 30.73–28.43%. Similarly, the plasticity index value decreased from 47.69–33.98%. As for Sun et al. (2021), they suggested that the plasticity index of the mixture (Chinese clay + sand) decreased as the sand content augmented. The variation of the liquid limit as a function of the plasticity index is showed in Fig. 10. One can clearly see that the liquid limit increases as the plasticity index increases. Note also that a linear relationship exists between these two variables, with a coefficient of correlation (R) equal to 0.97. The relationship between the liquid limit and plasticity index is described by Eq. 6.

$IP = 0.62WL-6.24$ (6)

3.4. Experimental validation

Table 6 and Fig. 11 presents a simple comparison between the experimental results and the predicted ones using the ANN model of the plasticity index of clay soil treated with dune sand. This same table indicates that the mean relative error (MRE) is very low (1.06%). The results obtained showed that this is a high performance model; it can be applied without carrying out any laboratory tests. This model is quite suitable for predicting the plasticity index of clayey soils treated with sand.

4. Conclusion

The artificial neural network (ANN) algorithm was used in this study to develop a model that allows predicting the plasticity index of sand-treated clayey soils. In addition, the effect of sand content on the plasticity index value of the mixture was also investigated. The findings of the study allowed drawing the following conclusions :

- This study confirms the good performance of the ANN model for predicting the plasticity index of clay soils treated with various contents of sand, with a high coefficient of determination (R^2). Indeed, the values R^2 found for the training, testing, and validation datasets were quite high; these values were respectively equal to 0.99, 0.97 and 0.99. In addition, the mean absolute error (MAE) had the lowest possible value (2.48%), which means that the ANN model is the appropriate choice for estimating the plasticity index.
- Increasing the dune sand content from 0 to 40% induced a better consistency limit parameter in the clayey soil of Boughezoul. In addition, the liquid limit and plastic limit values dropped respectively from74.5–45.7% and 33.66–22.6%. Moreover, the addition of 40% of dune sand diminished the plasticity index by 43% in comparison with the untreated clayey soil of Boughezoul. This engendered a behavior change from high plasticity clayey soil to low plasticity clayey soil.
- The models developed using the ANN method for estimating the plasticity index turned out to be highly performant, with a very low mean absolute error (1.06%) in comparison with the experimental results from the tests that were carried out on the soil treated with dune sand. Consequently, the model developed in this study can be applied in many geotechnical works with no need to carry out any laboratory tests.

Declarations

Conflict of interest:

The authors declare that they have no conflict of interest.

References

1. Arama, A.Z., Yucel .M., Akin. M. S., Dalyan. I. (2021).A comparative study on the application of artificial intelligence networks versus regression analysis for the prediction of clay plasticity. Arabian Journal of Geosciences, 14-534. Doi.org/10.1007/s12517-021-06894-x.
2. Alkroosh, I,. Al-Robay, A., Sarker, P ., Alzabeebee, S.(2021). Effect of sand percentage on the compaction properties and undrained shear strength of low plasticity clay. The Scientific Journal of Koya University, 9 (1) 16-20 .Dx.doi.org/10.14500/aro.10748.
3. Amiri ,M ., Hatami. F. (2022). Prediction of mechanical and durability characteristics of concrete including slag and recycled aggregate concrete with artificial neural networks (ANNs) .Construction and Building Materials 325 1-11. doi.org/10.1016/j.conbuildmat.2022.126839.
4. Amri, S., Akchiche, M., Bennabi, A., Hamzaoui, R. (2019). Geotechnical and mineralogical properties of treated clayey soil with dune sand. Journal of African Earth Sciences, 152 ,140–150. Doi.org/10.1016/j.jafrearsci.2019.01.010.
5. Atemimi, Y.K. (2020). Effect of the grain size of sand on expansive soil. International Key Engineering Materials ,857, 367-373.
6. Atemimi, Y.k., Snodi , L. N., Idan, A. A. H. (2021). Effect of sand on consistency limits of swelling soils. Second International Conference on Geotechnical Engineering-Iraq. Doi:10.1088/1755-1315/856/1/012023.
7. Bengraa, L. (2004). Contribution à l'étude de la stabilisation du gonflement par ajout de sable : application aux sols d'Oran. Thése de magister, université des sciences et de la technologie d'Oran.
8. Bouzid , F .(1997). Etude de l'aspect physico-chimique des caractéristiques mécanique d'une argile gonflante bentonite. Thèse de magister, université des sciences et de la technologie Houari Boumediene Alger.
9. Cabalar, A. F ., Mustafa, W. S . (2015). Fall cone tests on clay–sand mixtures. Engineering Geology, 192 , 154–165. Doi.org/10.1016/j.enggeo.2015.04.009.
10. Chavali, R.V.P. and Sharma, R.K. (2014). Influence of sand and fly ash on clayey soil stabilization. IOSR Journal of Mechanical and Civil Engineering (IOSR-JMCE) International Conference on Advances in Engineering & Technology (ICAET-2014), 36-40.
11. Chian, S. C., BI, j.(2021). Influence of grain size gradation of sand impurities on strength behaviour of cement-treated clay. Acta Geotechnica ,16,1127–1145. Doi.org/10.1007/s11440-020-01090-9.
12. Eyo .E.U., Abbey .S.J., Lawrence. T.T., Tetteh , F.K.(2022). Improved prediction of clay soil expansion using machine learning algorithms and meta-heuristic dichotomous ensemble classifiers.

Geoscience Frontiers ,13 1-18. doi.org/10.1016/j.gsf.2021.101296

13. Fattah, M. Y., Salim, N.M., Irshayyid, E. J.(2021) .Swelling behavior of unsaturated expansive soil. Transportation Infrastructure Geotechnology ,8,37–58 .Doi.org/10.1007/s40515-020-00112-z.
14. Frempong, E.M. (1995).A comparative assessment of sand and lime stabilization of residual micaceous compressible soils for road construction. Geotechnical and Geological Engineering,
15. ,181-198.
16. Gökalp, Z . (2009). Engineering characteristics of sand-clay mixtures used for clay cores of earth-fill dams. Clay Minerals ,44, 319–326. Doi: 10.1180/claymin.2009.044.3.319.
17. Goufı, A.E · Harichane, K., Harichane, Z ·, Ghrici, Z., Driss, A.A.E.(2022). Improvement of the geotechnical properties of a clay–sand mixture treated with lime. Innovative Infrastructure Solutions ,7 -114. Doi.org/10.1007/s41062-021-00705-8.
18. Goutham D.R., Krishnaiah., A.J.(2021). Application of artificial neural networking technique to predict the geotechnical aspects of expansive soil: a review. International Journal Engineering and Manufacturing, 6, 48-53. DOI: 10.5815/ijem.2021.06.05.
19. Hanif, M.H., Adnan, M., Shah, S.A.R., Khan, N.M., Nadeem, M., Javed, J., Akbar, M.W., Farooq, A., Waseem, M.(2019) .Rainfall runoff analysis and sustainable soil bed optimization engineering process: application of an advanced decision-making technique. Symmetry , 11, 1224. Doi.org/10.3390/sym11101224.
20. Harichane , K ,. Ghrici, M ,. Belhireche. H., Abdelghani.Y. (2017). Effet du sable de dune et de la chaux sur les propriétés géotechniques des sols argileux. Revue Scientifique de l’Ecole Nationale Supérieure des Travaux Publiques Francis Jeanson. Algérie équipement ,57 , 1-8.
21. Hudyma, N., Avar, B. B. (2006). Changes in swell behavior of expansive clay soils from dilution with sand. Environmental & Engineering Geoscience, 12(2),137–145. Doi.org/10.2113/12.2.137.
22. Jasim, M. M. ,. Al-Khaddar, R. M. ., Al-Rumaithi , A.(2019).Prediction of bearing capacity, angle of internal friction, cohesion, and plasticity index using ANN (case study of Baghdad, Iraq) .International Journal of Civil Engineering and Technology, 10 (1) 2670–2679.
23. Jirna, I.W., Setyawan, E ., Suwarno, E .(2017). The influence of sand addition on clay soil from deket kulon, deket subdistrict, lamongan viewed from the physical and shear strength characteristics changes. 1st International Conference on Vocational Education And Training.
24. Jjuuko, S., Kalumba, D. and Bagampadde, U., (2011). The use of locally available sand in stabilization of Ugandan clayey soils: Case study of clayey soil from Busega area, Uganda Institution of Professional Engineers 16th National Technology Conference (NTC 2011), Umaru.
25. Jyothi, D. N., Prasanna, H. S., Vishwanath. C. (2019).A study on index properties of kaolinite and bentonite sand mixtures. Proceedings of the 2nd International Conference on Emerging Research in Civil, Aeronautical and Mechanical Engineering (ERCAM).
26. Kaveh.A ., Khalegi , H.A. (2000) . Prediction of strength for concrete specimens using artificial neural network, Asian Journal of Civil Engineering, 2, (2) 1-13.

27. Kellouche ,Y ., Boukhatem ,B., Ghrici, M., Rebouh , R ,. Zidol , A.(2021) . Neural network model for predicting the carbonation depth of slag concrete. Asian Journal of Civil Engineering, 22, 1401–1414 .Doi.org/10.1007/s42107-021-00390-z.
28. Khelifa, T.1994. Contribution à l'étude de la stabilisation d'un sol gonflant par ajout de sable, cas des régions de Sidi-Aissa et de In-Amenas . Thèse de magister, université des sciences et de la technologie Houari Boumediene Alger.
29. Kolay, P.K., Ramesh, K.C. 2016. Reduction of expansive index, swelling and compression behavior of kaolinite and bentonite clay with sand and class C fly ash. Geotechnical and Geological Engineering 34, 87-101. Doi 10.1007/s10706-015-9930-4.
30. Kollaros, G., Athanasopoulou, A . (2016) .Sand as a soil stabilizer. Bulletin of the Geological Society of Greece ,50, 770-777.
31. Klinsky, L.M.G., Fabbri, G.T.P., Dos Santos Bardini, V.S. (2016) .Reuse of waste foundry sand mixed with lateritic clayey soils in pavement bases and sub-bases courses. 8th RILEM International Symposium on Testing and Characterization of Sustainable and Innovative Bituminous ,569- 582.
32. Lamara, M., Gueddouda, M.K., Goual, I . (2005). Stabilisation des sols gonflant par ajout de sable de dune. 2èmes journées d'études sur les sols gonflants, Tlemcen.
33. Louafı, B. and Bahar, R., (2012). Sand: An additive for stabilization of swelling clay soils, International Journal. Geosci, 3, 719-725.
34. Ma, Q., Cao, Z. , Yuan, P. (2018). Experimental research on microstructure and physical- mechanical properties of expansive soil stabilized with fly ash, sand and basalt fiber. Advances in Materials Science and Engineering, 9, 1-13. Doi.org/10.1155/2018/9125127.
35. Mekkiyah, H. M., Huat, B. B. K., Malek, M.A., Dis, M .N.(2011). Effect of mixing fine sand on the drained shear strength of completely decomposed granite soil. International Journal of Geomate, 1(1), 10-18.
36. Mekkiyah, H.M., Al-Khazragie, A. (2015).Behavior of clay soil mixed with fine sand during consolidation. Applied Research Journal ,1(8) ,437-443.
37. Nagaraj, H.B. (2016). Influence of gradation and proportion of sand on stress–strain behavior of clay–sand mixtures. International Journal of Geo-Engineering, 7 , 19. Doi.org/10.1186/s40703-016-0033-8.
38. Öncü , S ., Bilsel, H .(2018).Utilization of waste marble to enhance volume change and strength characteristics of sand-stabilized expansive soil. Environmental Earth Sciences, 77,461. Doi.org/10.1007/s12665-018-7638-5.
39. Phanikumar B.R., Dembla Supriya, Yatindra, A. (2021). Swelling behaviour of an expansive clay blended with fine sand and fly ash. Geotech Geol Eng ,39, 583–591. Doi.org/10.1007/s10706-020-01480-6.
40. Park, S ., Nong, Z. (2014).Effect of sand contents on plastic and liquid limits and shear strength of clays. Journal of the Korean Geotechnical Society, 30(2) ,65–76. Dx.doi.org/10.7843/kgs.2014.30.2.65.

41. Prakasha, K. S., Chandrasekaran, V. S.(2005). Behavior of marine sand-clay mixtures under static and cyclic triaxial shear. J. Geotech. Geoenviron. Eng ,131, 213-222.
42. Putra, P. P., Maruf, M. F., Ridwansyah, M. A., Kurniawan, R., Carisa, C. N.(2021). Perubahan potensi mengembang tanah ekspansif yang distabilisasi secara fisis dan mekanis. Construction and material journal ,3(1)1-14.
43. Qiang Zhou, Q,. Wang ,. F Zhu,F. (2016). Estimation of compressive strength of hollow concrete masonry prisms using artificial neural networks and adaptive neuro-fuzzy inference systems. Construction and Building Materials, 125 417–426. Doi.org/10.1016/j.conbuildmat.2016.08.064 0950-0618.
44. Ravi Shankar, A.U., Chandrasekhar, A. and Prakash Bhat H. (2012). Experimental investigations on lithomargic clay stabilized with sand and coir, Indian Highways ,40(2), 21-31.
45. Roy, T.K. (2013). Influence of sand on strength characteristics of cohesive soil for using as subgrade of road, Procedia - Social and Behavioral Sciences, 104, 218–224.
46. Sari Ahmed, B .,Gadouri, H , Ghrici, M .,Harichane , K.(2018). Best-fit models for predicting the geotechnical properties of FA–stabilised problematic soils used as materials for earth structures. International Journal of Pavement Engineering ,21 (7), 939-953 , Doi.org/10.1080/10298436.2018.1517874.
47. Shammat ,H. (2013). Study of expansive clayey sand (SC) soil in Sudan. Proceedings of the 6th International Young Geotechnical Engineers Conference.
48. Shrestha, S .(2016). Study of effects of coarse grain contents on Atterberg limits and expansiveness of the clay .Research Project, University of Southern Queensland.
49. Srikanth, V., Mishra, A.k .(20016). A laboratory study on the geotechnical characteristics of sand–bentonite mixtures and the role of particle size of sand. International Journal of Geosynthetics and Ground Engineering ,2 ,3 –10. Doi 10.1007/s40891-015-0043-1.
50. Sun, D ., Liu, X ., Cao, Y ., Gong, J., Hong, B. (2021).Determination of cost-effective sand mixing ratio for improvement of high liquid limit soil based on fuzzy comprehensive evaluation. Conf. Series: Materials Science and Engineering. Doi:10.1088/1757-899X/1203/3/032060.
51. Taleb Bahmed, I., Harichane, K., Ghrici. M., Boukhatem , B,. Rebouh , R., Gadouri, H. (2017). Prediction of geotechnical properties of clayey soils stabilised with lime using artificial neural networks (ANNs). International Journal of Geotechnical Engineering, 13(2),191–203. Doi : 10.1080/19386362.2017.1329966.
52. Yang, Y., Rosenbaum, M. S. (2002). The artificial neural network as a tool for assessing geotechnical properties." Geotechnical Engineering Journal, 20(2), 149-168.
53. Zhang ,Y., Li, J . , Zhang, C. (2021) .The mechanical properties and microstructure of reticulated red clay-sand mixture using x-ray diffraction. 2nd International Conference on Applied Physics and Computing. Doi:10.1088/1742-6596/2083/2/022081.

Tables

Table 1. Source of data.

Data source	Number of data	Data source	Number of data
Khelifa (1994)	36	Kollaros and Athanasopoulou (2016)	11
Frempong (1995)	4	Shrestha (2016)	4
Bouzid (1997)	5	Srikanth and Mishra (2016)	4
Bengraa (2004)	10	Jirna et al. (2017)	4
Lamara et al. (2005)	4	Shammat (2017)	6
Prakasha and Chandrasekaran (2005)	4	Hanif et al. (2019)	3
Hudyma and Avar (2006)	10	Atemimi (2020)	4
Mekkiyah et al. (2011)	5	Atemimi et al. (2021)	4
Ravi Shankar et al. (2012)	5	Chian and Bi (2021)	6
Roy (2013)	8	Fattah et al. (2021)	4
Park and Nong (2014)	14	Putra (2021)	6
Mekkiyah and Al-Khazragie (2015)	7	Sun et al. (2021)	5
Klinsky et al. (2016)	5	Zhang et al. (2021)	9
Kolay and Ramesh (2016)	6	Goufi et al. (2022)	4
Total number of data	197		

Table 2. Statistical parameters of data.

	Parameters	Unit	Minimum	Maximum	Range
Input	Liquid limit	%	19	219	56.82
	Plastic limit	%	10	105	26.08
	Sand content	%	0	100	26.70
Output	Plasticity index	%	3.9	155	30.74

Table 3. Relative errors between experimental and the ANN predicted of plasticity index

Author	Sand (%)	LL (%)	PL (%)	PI-Exp (%)	PI- ANN (%)	Error (%)
Gokalp (2009)	0	51.5	27.33	24.17	23.73	1.82
	10	44.59	25.55	19.04	18.79	1.31
	20	42	22.72	19.28	19.09	0.99
	30	36.8	18.57	18.23	18.26	0.16
	40	33.45	17.8	15.65	16.06	2.62
	50	30.01	17.59	12.42	13.40	7.89
Jjuuko et al .(2011)	0	49.4	18.9	30.5	30.14	1.18
	20	37	14.4	22.6	22.36	1.06
	40	30.9	15.7	15.2	15.71	3.36
	60	26.3	15.7	10.6	12.03	13.49
Öncü and Bilsel (2018)	0	65	36	29	28.84	0.55
	50	32	20	12	13.00	8.33
Jyothi et al. (2019)	0	67.51	30.12	37.39	37.53	0.37
	10	64.96	28.87	36.09	36.06	0.08
	20	58.34	26.92	31.42	31.14	0.89
	30	53.64	25.3	28.34	28.00	1.20
	40	50.73	24.61	26.12	25.80	1.23
	50	42.87	22.23	20.64	20.55	0.44
	60	38.09	19.29	18.8	18.95	0.80
	70	36.33	18.65	17.67	18.00	1.87
Average error						**2.48**

Table 4. Geotechnical characteristics of the used materials.

Properties	Symbols	Clay	Dune sand	Standards
<80 µm	(%)	99.2	-	NF P 94 (056-057)
< 2 µm	(%)	47.4	-	
Specific gravity	Gs	2.51	2.62	NF P 94-054
Natural water content	Wn(%)	25.8	-	NF P 94-050
Liquid limit	LL (%)	74.50	-	NFP 94-051
Plastic limit	PL (%)	33.66	-	
Plasticity index	PI (%)	40.84	-	
Consistency index	CI (%)	1.19	-	
Methylene blue value	MBV	5.5	0.25	NFP 94-068
Specific surface area	SSA (m^2/g)	115.5	5.25	
Optimum moisture content	Wop (%)	20.1	-	NFP 94-093
Maximum dry density	(t/m^3)	1.61	-	
Sand equivalent	SE(%)	-	55.32	NF EN 933-8

Table 5. Variation of consistency limit with different percentage of dune sand.

Dune sand (%)	LL (%)	PL (%)	IP (%)
0	74.5	33.66	40.84
10	66	31.48	34.52
20	58	29.92	28.08
30	49.9	25.13	24.77
40	45.7	22.6	23.1

Table 6. Comparison between experimental results and predicted results of plasticity index.

Figures

Dune sand (%)	PI-Exp (%)	PI- ANN (%)	Error (%)
0	40.84	41.33	1.20
10	34.52	34.46	0.17
20	28.08	27.7	1.35
30	24.77	24.4	1.49
40	23.1	22.85	1.08
Average error			**1.06**

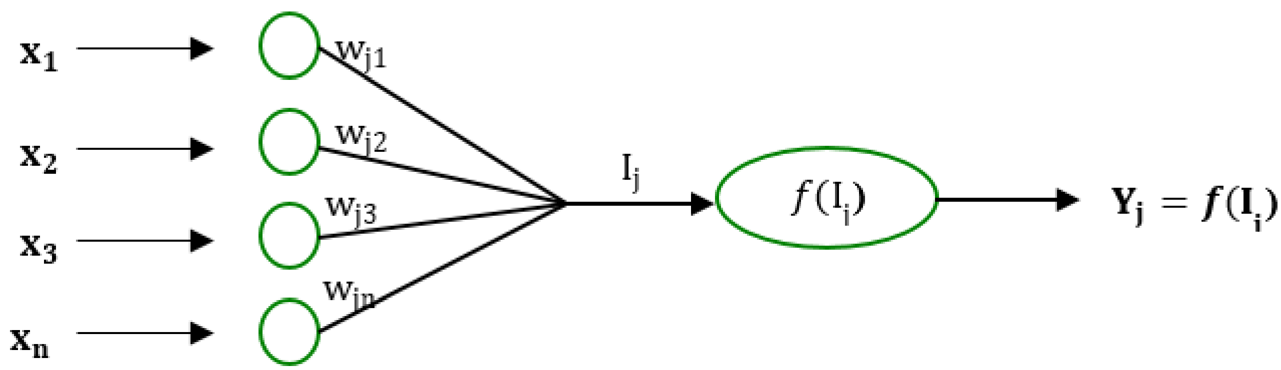

Figure 1

Schematic the structural operation of a ANN network.

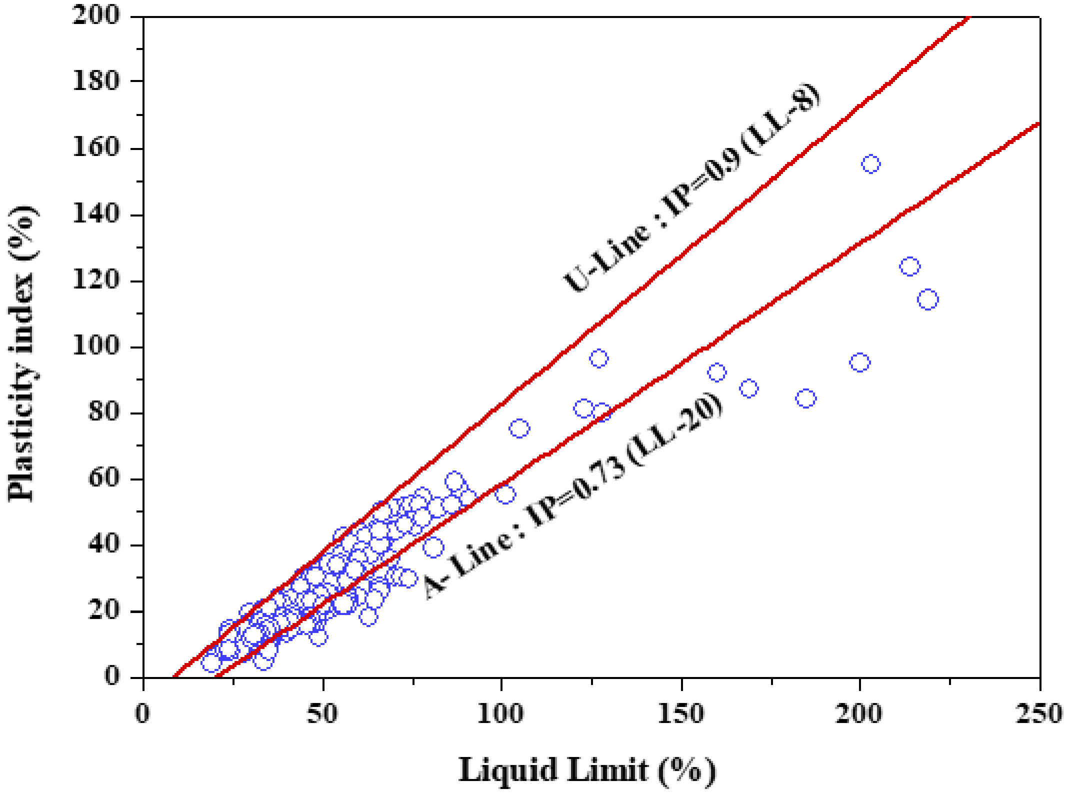

Figure 2

Location data on the plasticity chart.

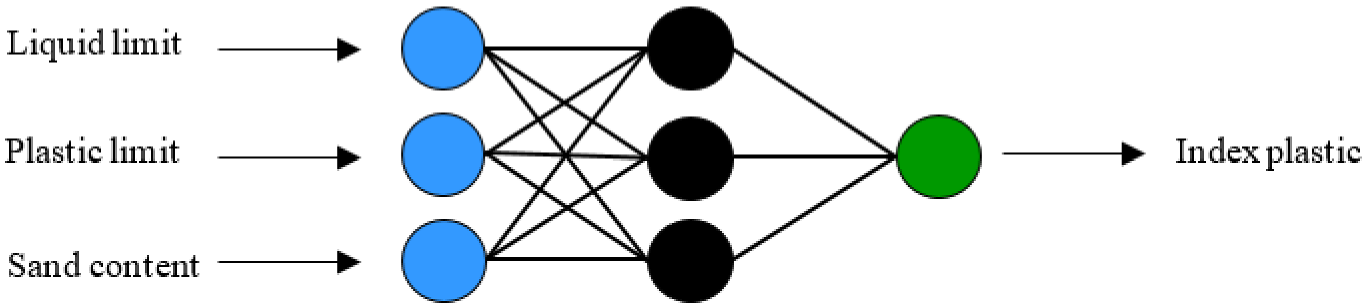

Figure 3

Neural network architecture for plasticity index prediction.

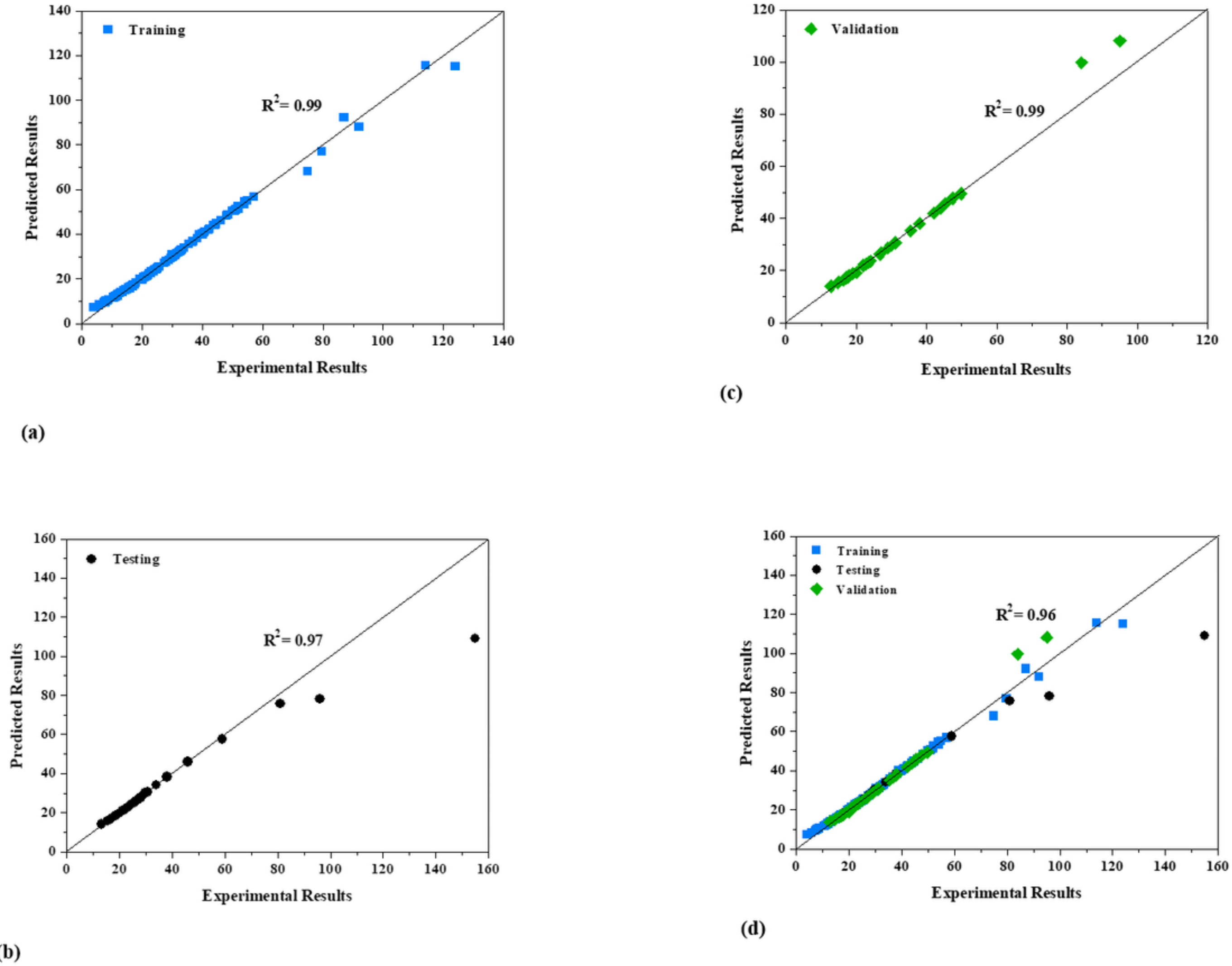

Figure 4

Comparaison between experimental results predicted for plasticity index

(a) Training, (b) Testing, (c) Validation, (d) All sets.

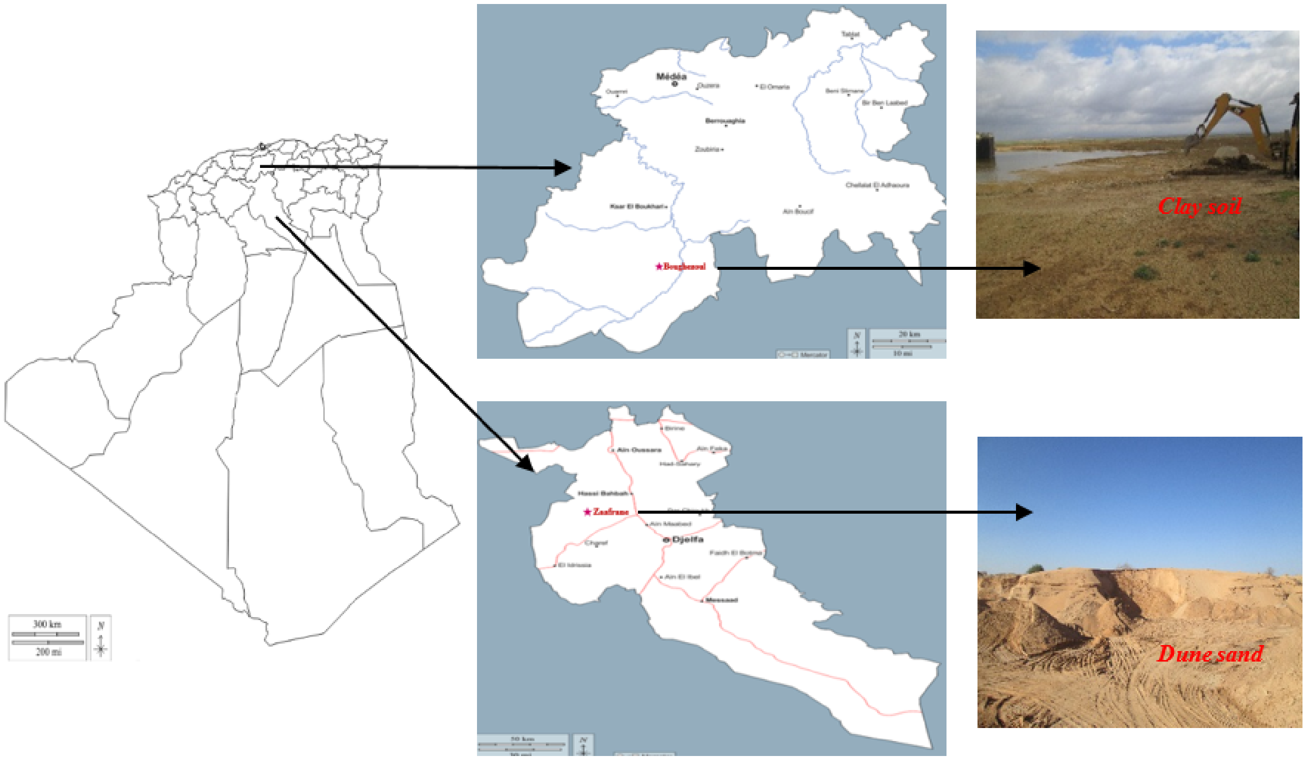

Figure 5

Location of the studied materials.

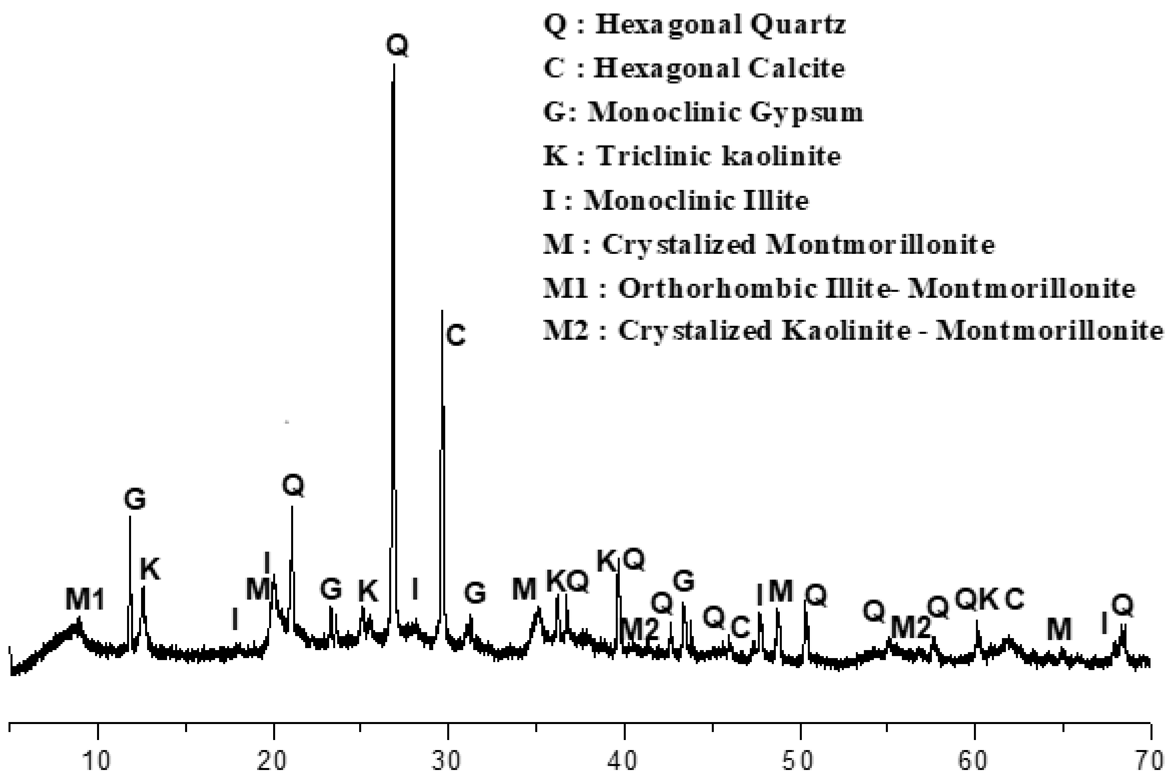

Figure 6

X-ray diffraction of the clay soil.

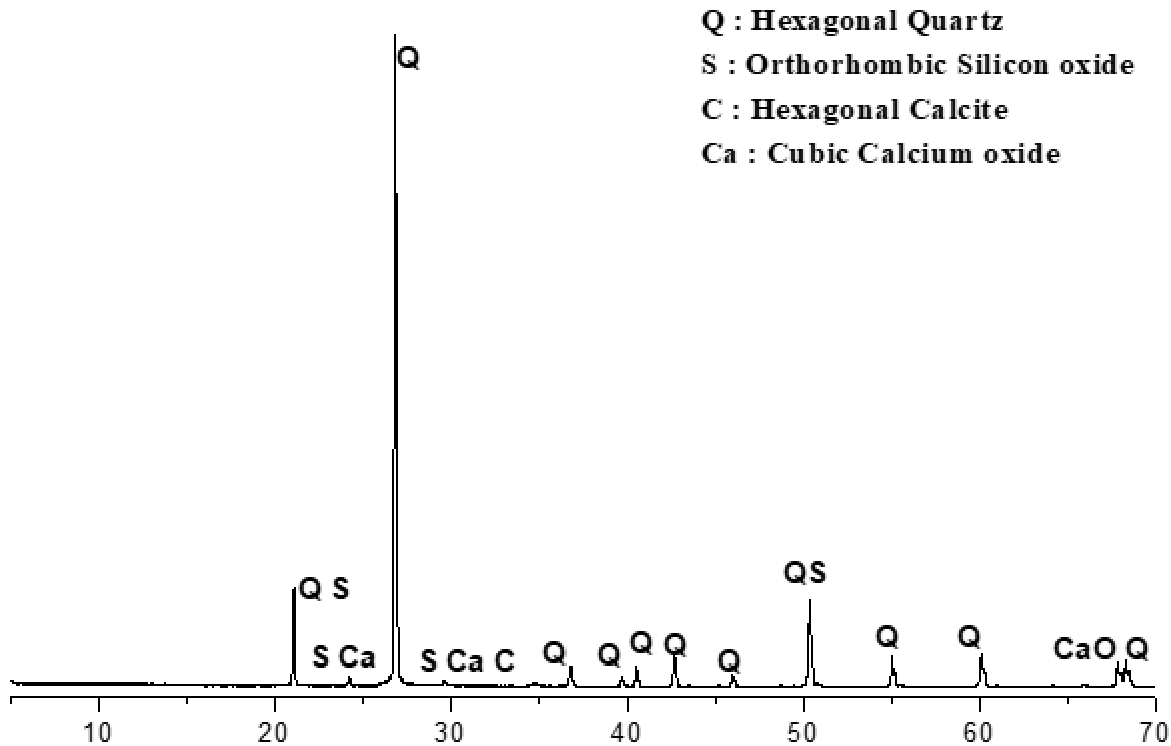

Figure 7

X-ray diffraction dune sand.

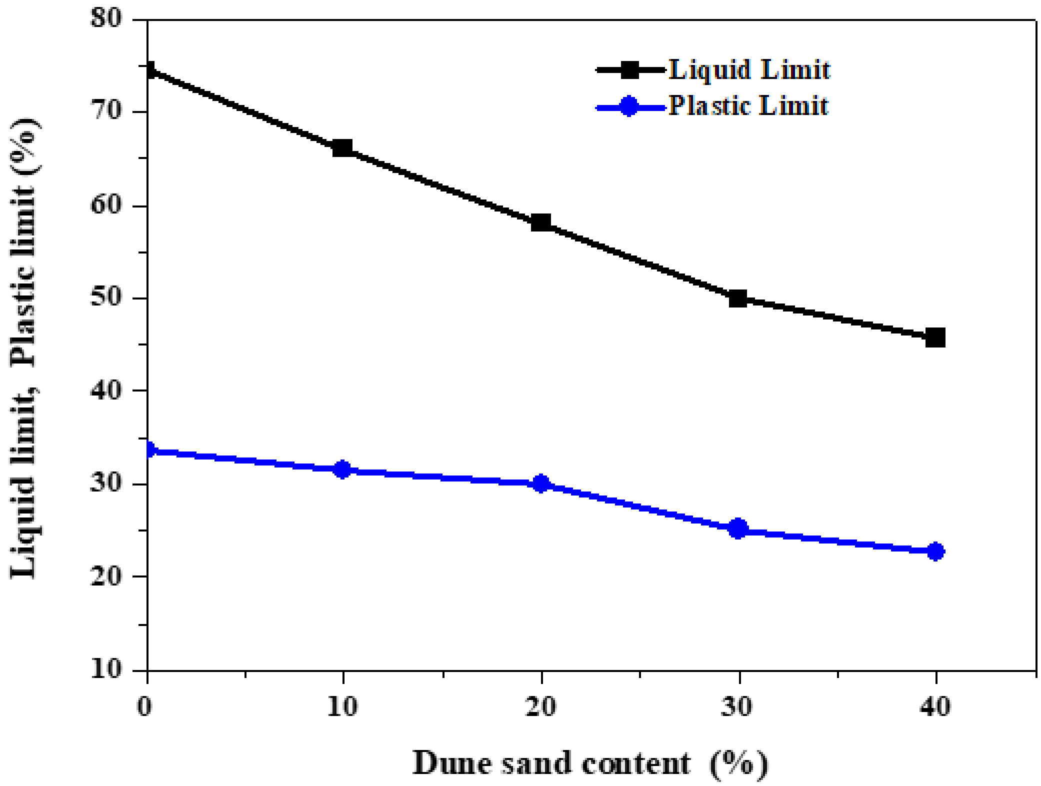

Figure 8

Variation of liquid limit, plastic limit with different percentage of dune sand.

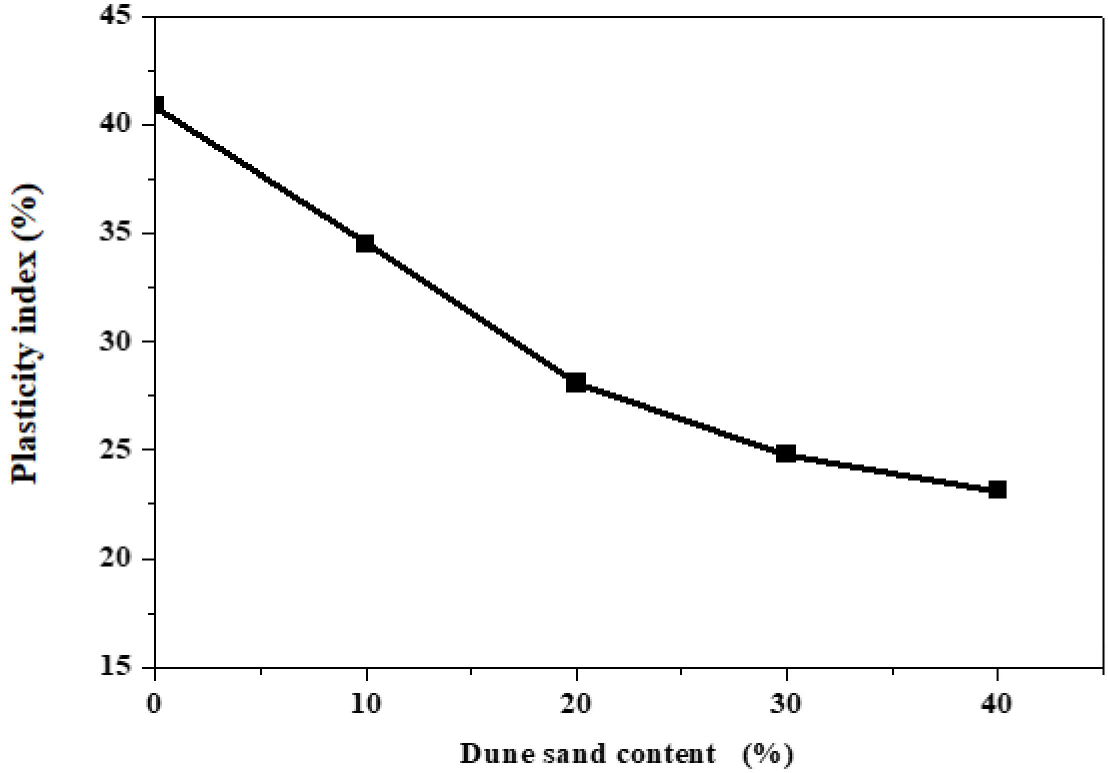

Figure 9

Variation of plasticity index with different percentage of dune sand.

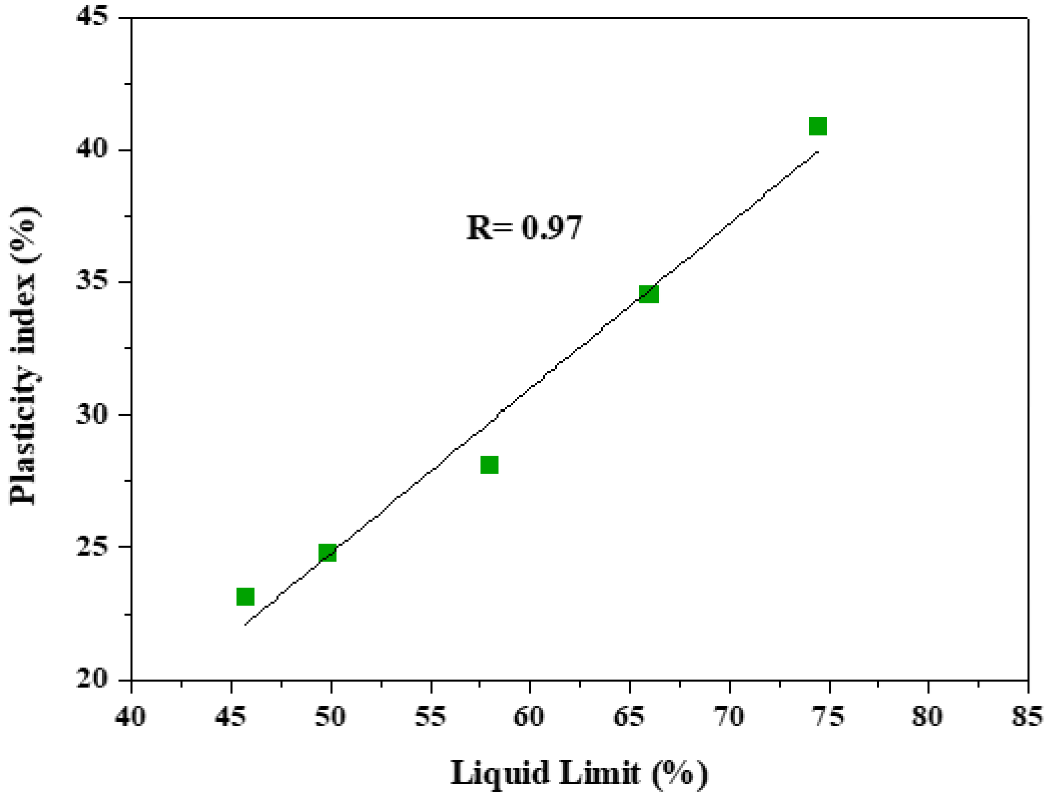

Figure 10

Evolution liquid limit with plasticity index.

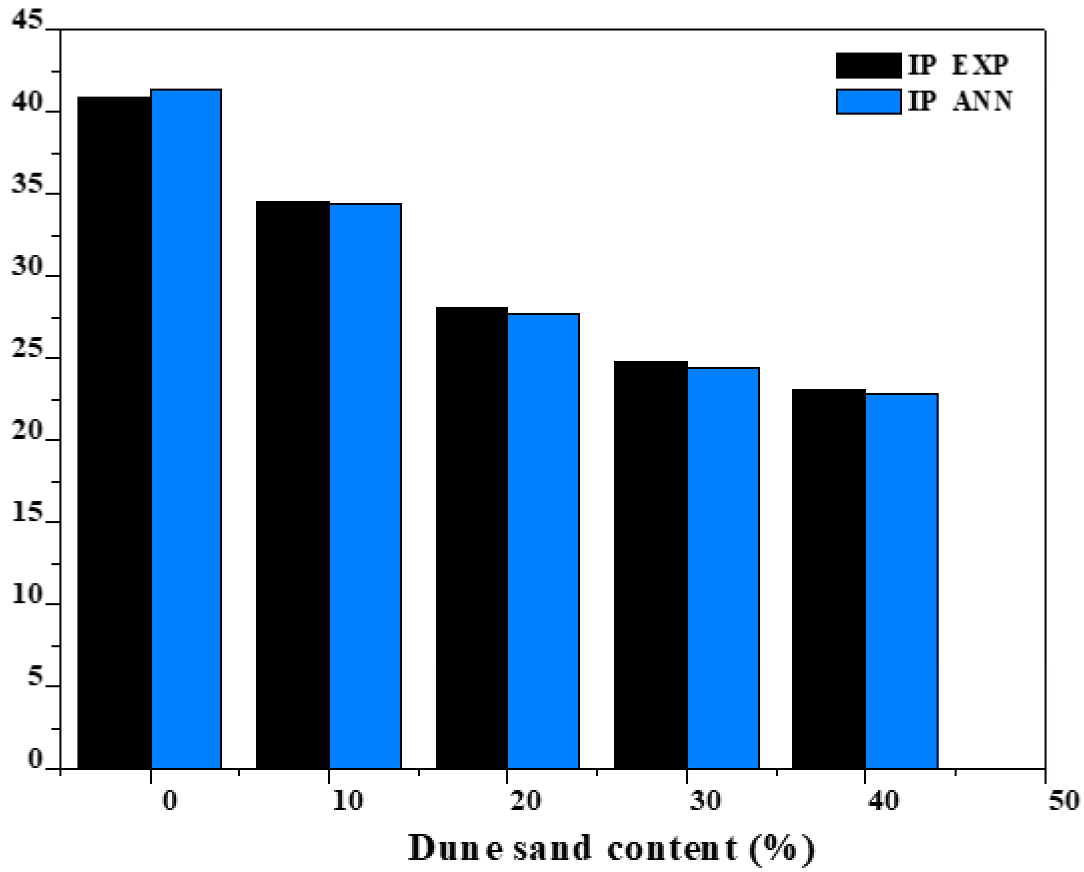

Figure 11

Comparison between the experimental results and the predicted values by ANN model for plasticity index treated with dune sand .