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Study of some applications of the technique of Artificial Neural Networks (ANNs) in geotechnical engineering

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Abstract. The application of Artificial Neural Networks (ANNs) in geotechnical engineering has grown significantly since the early 1990s. ANNs have been used to address various geotechnical engineering problems (e.g., geotechnical classification, geotechnical properties prediction, site characterization, earth retaining structures, settlement of structures, foundation and slope stability) and have shown a certain degree of success. This article presents an overview of some ANN case applications for solving specific geotechnical engineering problems and discusses the use of ANNs for the indirect determination of geotechnical properties based on known index properties. The use of ANNs is evaluated for soils from different regions to predict one-dimensional compressibility of soft soils and permeability of saturated soils. The article also explores the use of ANNs in predicting the consistency limits of fine-grained soils and the calibration required in the Time Domain Reflectometry (TDR) technique used to measure soil moisture. The studies reviewed in this article indicate that ANNs have potential as an alternative to empirical correlations for predicting soil properties based on their index properties, for soils from various regions of Brazil and other countries.

Keywords: Artificial Neural Networks, compression index, permeability, consistency limits of soils, TDR calibration.

1 Introduction

Artificial neural networks (ANNs) have been used for a variety of case applications in geotechnical engineering during the past two decades (Shahin et al. [1,2], Pooya et al. [3], Park and Lee [4], Juwaied [5], Moayedi et al. [6], Rautmare et al. [7]). ANNs have been successfully used to support various geotechnical engineering challenges, including geotechnical classification, geotechnical properties prediction, site characterization, earth retaining structures, settlement of structures, foundation and slope stability. These applications indicate the versatility and effectiveness of ANNs in solving problems within the geotechnical engineering domain. The good performance results are generally assessed from statistical techniques.

This study addresses the application of ANNs as a tool for estimating geotechnical properties based on previously known index parameters. The investigation includes case studies involving soils from various regions of Brazil as well as other countries, focusing on the prediction of properties such as one-dimensional compressibility and the coefficient of permeability. In addition, the study explores the potential of ANNs for estimating the consistency limits of predominantly fine-grained soils and the calibration required in the Time

Domain Reflectometry (TDR) technique used to measure soil moisture. Further information regarding the architecture and configurations of the employed ANN models can be found in the references cited in the paper.

2 Artificial Neural Network (ANN) technique

Artificial neural networks are machine learning (ML) techniques inspired by the functioning of the nervous system, aiming to computationally simulate the human brain's learning process in acquiring and processing knowledge. The initial development of these networks dates back to the 1940s, when McCulloch and Pitts [8] proposed the first mathematical model of an artificial neuron, which is the basic processing unit of ANNs.

In ANNs, data flows from the input layer to the output layer through one or more hidden layers. Each layer is composed of artificial neurons (nodes or units) that receive input data, process it, and pass the output data to the next layer. The primary layers (input, hidden and output) work together to extract features, transform data, and make predictions. Each neuron applies a mathematical function to input data and is connected to other neurons through synaptic weights, which determine the influence of each connection. These neurons are organized into layers, typically an input layer, one or more hidden layers, and an output layer. The input layer and output layer are predefined by the problem investigation, but the hidden layers are not. Model architecture requires the selection of the optimal number of hidden layers in the ANNs and the determination of the optimal number of neurons in each layer. Figure 1(a) illustrates a simplified model of an artificial neuron, while Figure 1(b) presents a neural network with three layers. A neuron's output depends on the used activation function, making it essential for the performance of the whole network. Commonly used activation functions include linear, ReLU (Rectified Linear Unit), sigmoid, Gaussian, and hyperbolic tangent. ANNs are used to solve a wide variety of tasks, including classification and regression. For them to function effectively, it is essential to define a network architecture, which includes the number of layers and neurons per layer, the type of activation function, and the connection pattern between neurons. Currently, these networks are applied to various types of data, such as tabular data, text, images, audio, and video. Their use spans a wide variety of fields, including healthcare, economics, manufacturing, geotechnical engineering, and others, standing out as an important tool in artificial intelligence.

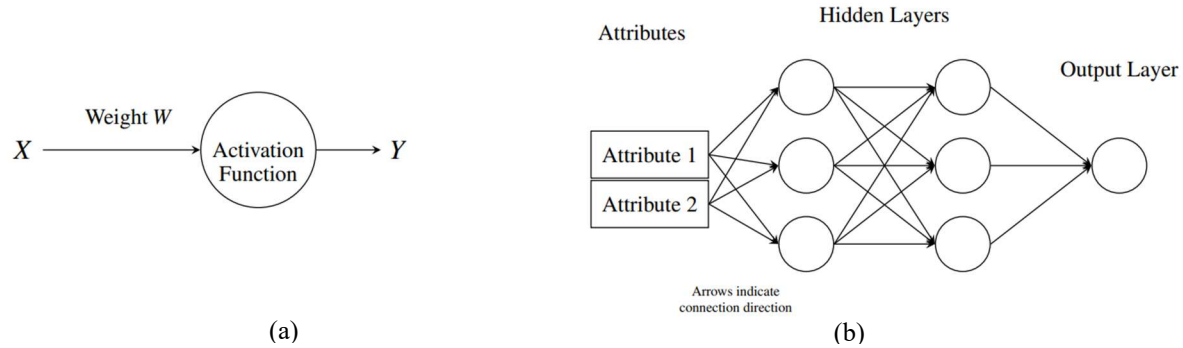


Figure 1. (a) Artificial neuron model and (b) example of a Neural Network with three layers

3 Some examples of ANN case applications in geotechnical engineering

3.1 Case 1: Use of ANNs to predict soil consistency limits of soft soils

The Liquid Limit (LL), together with grain size distribution, is fundamental in geotechnical engineering for classifying fine-grained soils and assessing their hydro-mechanical properties. It can be determined by two standardized methods: the Casagrande cup (LL_{cup}), traditionally the most used, and the Fall Cone (LL_{FC}), which reduces operator dependence (Haigh [9]). Most classifications and correlations rely on LL_{cup}, especially in countries such as Brazil, Portugal, the U.S., and India. However, the increasing use of LL_{FC} in practice emphasizes the need for reliable LL_{cup}-LL_{FC} correlations allowing estimation of LL_{cup} from LL_{FC} and vice versa. Recent studies highlight the potential of ANNs and other ML techniques to predict soil consistency limits.

Zolfaghari et al. [10] used ANNs with Iranian soil data and found good LL prediction accuracy when incorporating soil properties, topography, and remote sensing data. Diaz et al. [11] applied ML algorithms to

correlate LL_{FC} and LL_{cup} using plastic limit (PL) and grain size distribution, achieving better results than linear models, especially for LL > 30. However, O'Kelly et al. [12] challenge the proposed linear correlation by Diaz et al. [11], highlighting its inconsistency with previously investigated data, which typically show $LL_{cup} \leq LL_{FC}$. Their critical analysis emphasizes the need for predictive models to be grounded in physical principles, avoiding statistical generalizations without adequate experimental validation. The debate reinforces that, although AI techniques are promising, they must be contextualized within physical meaning to ensure reliability. Arama et al. [13] predicted the plasticity index (PI) from LL using ANNs and avoided the need for direct PL measurement, outperforming empirical methods. On the other hand, O'Kelly and Soltani [14] criticize the PI–LL correlations proposed by Arama et al. [13] due to the mineralogical diversity of clayey soils and the inconsistency when compared to other studies. Edib et al. [15] compared ANNs and Genetic Programming (GP) in treated soils, with ANNs showing lower errors and higher predictive performance. Aydın et al. [16] applied ML techniques to classify soils using a dataset of 805 samples. Ensemble learning algorithms, such as XGBoost and LightGBM, achieved accuracies of up to 90%, outperforming traditional classification methods. The study concluded that ML could optimize soil classification by reducing both time and cost, with boosting algorithms standing out, alongside the importance of proper input data processing for model performance. Qamar et al. [17] developed ANNs and multivariate linear regression (MLR) models to predict the LL and plastic limit PL based on materials passing through the Nº. 200 sieve, which suggested to be more suitable than those retained on the Nº. 40 sieve. A total of 120 soil samples were analyzed through grain size distribution and Atterberg limit tests, showing that 45% of the samples changed classification when the sieve was changed. The predictive models achieved high accuracy (R^2 = 0.999), indicating strong generalization capability.

3.2 Case 2: Use of ANNs to predict calibrations for Time Domain Reflectometry (TDR)

The Time Domain Reflectometry (TDR) technique measures soil moisture (θ) based on the variation in the propagation speed of high-frequency electromagnetic pulses, which affects the apparent dielectric constant (K_a). From K_a, θ can be estimated using calibration equations or pedotransfer functions (PTFs) derived from laboratory or field data (Andreu et al. [18]). TDR enables rapid, non-destructive, in situ measurements, supporting sensor and system improvements (Kojima et al. [19]; Comegna et al. [20]) and applications such as continuous field monitoring (Sheng et al. [21]) and erosion or stability studies (Zhang et al. [22]). Machine learning, particularly ANNs, has been applied to TDR calibration as a more efficient alternative to conventional complex models (Scarpetta et al. [23]; Li et al. [24]; Qiu et al. [25]).

Persson et al. [27] first used ANNs as PTFs to estimate θ from K_a, achieving better results than conventional equations, later proposing a general calibration including soil density and clay content [28]. These MLP models used feedforward architectures with a single hidden layer (8–11 neurons). Namdar-Khojasteh et al. [29] also applied MLPs with K_a, density, and clay as inputs; the best network (3-10-1 architecture) achieved R^2 = 0.998 and RMSE = 0.00433 m^3/m^3, outperforming empirical models and generalizing well to unseen soils. Similarly, Arsoy et al. [30] estimated θ with K_a, dry density, specific gravity, and fines, obtaining RMSE = 0.007 cm^3/cm^3, superior to traditional models (0.015–0.033 cm^3/cm^3), especially for sandy soils.

Zanetti et al. [31] trained ANNs with five soil types for general TDR calibration. The best model, with 13 hidden neurons and a tan-sigmoid activation function, slightly outperformed third-order polynomial (Topp-type) equations. Organic matter was the most influential input, followed by sand, clay, and density; silt showed little effect. Results ranged from RMSE = 0.0126–0.0237 g/g and R^2 = 0.9083–0.9891, with superior performance in sandy soils.

Overall, studies indicate that ANNs consistently outperform traditional regression approaches in calibrating TDR sensors for soil moisture estimation. This superiority is due to the ANN's ability to integrate multiple soil properties and capture complex nonlinear relationships between K_a and θ, resulting in greater accuracy and robustness, especially in contexts with high textural variability. Furthermore, models with simple architecture, such as multilayer perceptron with a single hidden layer, have demonstrated excellent generalization capability, reinforcing the practical feasibility of applying this approach under different field conditions.

3.3 Case 3: Use of RNAs to predict one-dimensional compressibility of soft soils

The compression index (C_c) is a useful parameter for predictions of consolidation settlement of soft soils

under applied loads. Since direct measurement of C_c can be time-consuming, several studies have developed empirical correlations using index properties such as initial void ratio (e_0), natural water content (w_n) and Atterberg limits (LL, PI). These correlations, often derived from linear regression models, show significant variability across different datasets (Azzouz et al. [32]; Kootahi and Moradi [33]), underscoring the need for careful selection and local calibration. The LL obtained via the Casagrande method, $LL_{cup,}$ is frequently used as an input index property in such models.

To overcome limitations inherent in traditional regression, many researchers have adopted ANNs for predicting C_c in soft clays. Studies by Kolay et al. [34] and Ozer et al. [35] demonstrated that ANNs trained with geotechnical index data can produce reliable C_c estimates. Park and Lee [36] showed strong ANN performance using input parameters like e_0, LL, w_n, and PI. Kalantary and Kordnaeij [37] successfully applied ANNs to clays from northern Iran, while Kurnaz et al. [38] found improved predictive accuracy in a dataset of 246 samples using LL, PI, e_0, and w_n. Oliveira Filho et al. [39] compared ANN performance against traditional empirical correlations using data from 225 oedometer tests on Brazilian coastal soils and confirmed the superior predictive capacity of ANN models.

Overall, ANN-based approaches have shown greater generalization and adaptability compared to fixed empirical formulas, especially in contexts with diverse geological conditions. Their ability to learn from new data makes them a powerful tool for estimating C_c values during preliminary geotechnical investigations. Consequently, ANNs are recommended as a robust alternative for assessing the variability of soft soil compressibility both in Brazil and internationally.

3.4 Case 4: Use of ANNs to predict the permeability coefficient of saturated soils

The saturated permeability coefficient (k_{sat}) is a key parameter in geotechnical engineering, affecting drainage, slope stability, and groundwater management. Since direct determination is costly and time-consuming, predictive models using soil index properties have been developed, with ANNs showing strong capability to capture nonlinear relationships.

Wrzesiński and Markiewicz [40] applied an MLP ANN (6-8-1 architecture) for sandy soils, using soil type, relative density, void ratio, and d10, achieving ±4% mean error. Tizpa et al. [41] used an MLP (10 neurons) with Atterberg limits, grain size, and compaction degree as inputs, obtaining $R^2 = 0.99$, with compaction, fines, and fineness modulus as most influential. Trejo-Alonso et al. [42] trained ANNs with 900 samples, two hidden layers, and soil parameters as inputs, achieving $R^2 = 0.9725–0.9780$, outperforming pedotransfer functions and prior ANN studies.

Hybrid approaches also proved effective: Kharnoob et al. [43] used ANN-PSO ($R^2 = 0.987$, RMSE = 0.0003) and ANN-GA ($R^2 = 0.977$, RMSE = 0.0004) with grain size and void ratio inputs, with d10 as the most relevant variable. Even a simpler two-layer MLP performed well ($R^2 = 0.861$). Akbulut [44] developed a single-hidden-layer ANN (12 neurons) for coarse soils with fines, sand, gravel, and grain sizes as inputs, outperforming MLR and empirical formulas (Hazen, Slichter).

Pham et al. [45] compared ANN, SVM, and RF with 84 Vietnamese samples; ANN (10 neurons) was close to RF (R = 0.845 vs. 0.851), showing it as a less intensive alternative. Bui et al. [46] improved ANN with TLBO optimization (two hidden layers, 12 and 8 neurons), achieving R = 0.905 vs. 0.845 in the base ANN. Singh et al. [47] tested MLP, CANFIS, SVM, DT, RF, and wavelet models; W-MLP performed strongly, while W-RF had the highest accuracy, confirming ANN robustness.Yilmaz et al. [48] compared ANNs and ANFIS with grain size inputs; ANN ($R^2 = 0.933$) was outperformed by ANFIS ($R^2 = 0.973$). Williams and Ojuri [49] compared ANN (10 neurons) and MLR across soil types, with ANN showing clear superiority ($R^2 = 0.955$ vs. 0.404), highlighting fines as the most influential input.

Overall, ANN-based models, especially MLPs with multiple hidden layers, demonstrate excellent generalization and predictive accuracy for k_{sat} estimation. Their ability to integrate diverse soil parameters and capture nonlinearities confirms their reliability and practicality for geotechnical applications.

4 Discussion and conclusion

This study demonstrated that ANNs hold significant potential as an alternative to traditional empirical correlations for predicting geotechnical properties across different regions of Brazil and abroad. While classical correlations exhibit limitations in their applicability to local databases, ANNs stand out due to their learning

capacity and adaptability to new information, making them less sensitive to the natural variability of geological and geotechnical conditions. The comparative analysis of the reviewed studies reveals that, in general, ANNs exhibit superior performance compared to linear and non-linear regressions, reducing prediction errors for parameters such as consistency limits, compression index, coefficient of permeability and TDR calibrations. In some instances, alternative ML techniques, such as Random Forest, Support Vector Machines and hybrid models (e.g., ANN-PSO, TLBO, ANN-GA) achieved similar or slightly better results, but their increased complexity and computational cost render them more appropriate for advanced research or scenarios demanding maximum predictive performance, where data availability and model interpretability are secondary. This suggests that the choice of the most suitable method should consider not only statistical accuracy but also factors such as implementation complexity, data availability, and model interpretability. A comparative synthesis of these approaches is presented in Table 1. The main challenges are: (*i*) the need for standardization of input variables, as different studies adopt distinct combinations of geotechnical indices; (*ii*) the scarcity of sensitivity analyses and model explainability, which hinders the identification of the most influential variables; and (*iii*) the lack of systematic comparisons among different ML techniques for similar problems. These aspects indicate that future research directions should advance toward broader comparative studies from diversified databases.

Table 1. Summary of some compilated studies for geotechnical property prediction using ML methods

Case	References	ML Techniques	Accuracy / Results	Contributions
Case 1	[10], [11], [13], [15], [16], [17].	ANNs, ML (XGBoost, LightGBM), GP, MLR.	ANNs and ML outperformed linear regressions, R^2 close to 1 in some cases. Results were sensitive to granulometric data. Some correlations showed physical inconsistencies.	Validated ANNs for LL/PI prediction, highlighted superiority over empirical methods, emphasized importance of input data.
Case 2	[27, 28], [29], [30], [31].	ANNs (MLP, feedforward).	ANNs outperformed conventional empirical equations with high R^2 (~0.99) and very low RMSE (<0.01). Better performance in sands but good generalization in other soil types.	Introduced ANNs for TDR calibration, validated applicability in different soil types, and identified key input variables.
Case 3	[34], [35], [36], [37], [38], [39].	ANNs (MLP), comparisons with empirical correlations.	ANNs outperformed empirical correlations, with consistent results for other datasets and geological conditions. Reliable predictions for practical applications.	Validated ANNs as a robust alternative to empirical formulas, confirming applicability in regional contexts.
Case 4	[40], [41], [42], [43], [44], [45], [46], [47], [48], [49].	ANNs (MLP), (ANN+PSO, ANN+GA, TLBO-ANN), SVM, RF, ANFIS.	ANNs achieved high R^2 (up to 0.99). Hybrid models further improved performance. RF and ANFIS sometimes outperformed ANNs, but with greater complexity.	Confirmed robustness of ANNs for k_{sat} prediction, showed hybrids improve accuracy, and emphasized importance of key variables such as fines content and soil density.

From a practical standpoint, it is recommended that ANN models for estimating soil properties be employed in preliminary project phases or complementary field studies, serving as auxiliary tools to reduce costs and timelines. The incorporation of hybrid models, the use of robust pre-processing techniques, and the sharing of international geotechnical databases can contribute to establishing ANNs as a reliable resource to support geotechnical investigations and projects.

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Authorship statement. The authors hereby confirm that they are the sole liable persons responsible for the authorship of this work, and that all material that has been herein included as part of the present paper is the property (and authorship) of the authors.

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