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A Multi-Layer Perceptron (MLP) Neural Network Approach for Predicting Pressuremeter (PMT) Test Results in Geotechnical Engineering

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ABSTRACT

This study proposes a hybrid machine learning approach using a Multi-layer Perceptron Neural Network (MLP) to predict soil pressuremeter parameters, leveraging a database of 120 soil samples from the Algeria railway line project. The MLP model demonstrated superior performance, achieving a high coefficient of determination ($R^2 > 0.93$) and low RMSE, indicating strong agreement between predicted and experimental values. Comparative analysis with multiple regression highlighted the MLP's efficiency in prediction speed and accuracy, though its "black-box" nature limits interpretability of individual parameter influences. While regression provided explicit equations for variable effects, the study underscores the importance of expanding the database with representative inputs to further enhance predictive reliability. The results support MLP as a robust tool for geotechnical forecasting, balancing precision with computational efficiency.

1 Introduction

The study of soil behavior is complex and requires the development of a large number of laboratory and field tests [1, 2]. In-situ tests have the advantage of testing the soil in its environment, avoiding the redesign of sampling required for

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laboratory tests [3]. However, this does not mean that the soil can be considered intact at the time of the test, since the installation of the device causes either back drafting if the device is driven, or a release, if it is installed in a borehole.

In situ tests, requiring most often bulky and sometimes heavy equipment, are mainly based on empirical considerations, lacking theoretical foundations. Soil properties are not directly identified from these considerations, and in which the actual stress or deformation paths and the corresponding spatial and drainage boundary conditions are usually unknown and always difficult to define. Laboratory tests allow for better control of drainage and loading conditions and a broader exploration of the laws of soil behavior [4, 5]. However, these tests are often slow and costly, and are carried out on small, more or less reworked samples that do not always represent the state of the in-situ soil [6]. The corresponding experimental procedures are complex, but they can provide good results only if the soils tested are representative of the real soils under the structures.

The pressuremeter test is a widely used device for in-situ soil testing in some countries, for most geotechnical projects, especially for foundation projects [7, 8, 9]. The test was invented by Kögler around the 1930s [10], but became better known after its use by [11]. It has been standardized since the end of the 1960s and the current operating mode is specified by the European standard NF EN ISO 22476-4 [12] and the American Standard D 4719 [13]. The routine interpretation of the pressuremeter test consists of calculating a pressuremeter modulus Ménard (EM), the limit pressure (PLM), and the creep pressure (Pf). The determination of these parameters, however, requires equipment that is usually voluminous and sometimes heavy, skilled labor and considerable time. This generally results in a relatively excessive cost.

Several researchers have proposed estimation models based on artificial neural networks (ANNs). In this context, our work introduces a hybrid Multi-layer Perceptron Neural Network (MLP) model to predict pressuremeter parameters, leveraging an enriched database of geotechnical properties. The proposed MLP approach has the advantage of a very rapid estimation of the pressuremeter modulus and the limit pressure of a soil. These two parameters are very useful in the calculation of the bearing capacity, rupture and deformability of geotechnical structures

2 Materials and methods

2.1 Ménard pressuremeter: procedure and results

The probe is placed in a pilot hole made prior to testing with a hand auger or other means of drilling, depending on the nature of the soil. This ensures that the in-situ soil is minimally affected and that the borehole diameter can best match the diameter of the probe [14, 8]. Fig. 1 shows the composition of a pressuremeter. It essentially consists of: a pressure-volume controller, a probe and coaxial tubing.

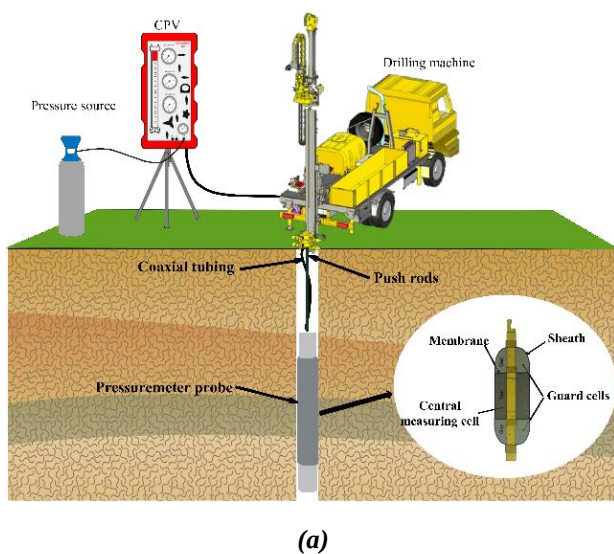


Fig. 1 - (a) Procedure of the Ménard pressuremeter test, (b) Pressuremeter tests in the study site

According to the NF EN ISO 22476-4 standard [12], the test consists in applying progressively in steps on the borehole wall, a constant step pressure Δp close to one tenth of the estimated limit pressure. Each pressure is kept constant in the

measuring and guard cells for an instant $\Delta t = 60$ seconds. At each step, the pressure applied and the volume injected into the probe are displayed and recorded at 1, 15, 30 and 60 seconds.

The raw measurement results obtained in the field by the operator are corrected for the compressibility of the system, the inherent resistance of the membrane and the water level in the pipes. These corrections are subtracted from the gross test curve to obtain the corrected or net test curve. The test curve is expressed as the relationship between the pressure applied to the ground and the displacement of the probe wall (Curve 1, Fig. 2). Based on this test, the interpretation provides: a pressuremeter modulus (E_M) determined on the linear part of the pseudo-elastic phase (Eq. 1); the limit pressure (P_{LM}), which corresponds to the breaking strength of the soil obtained for a large deformation of the cylindrical cavity; and the creep pressure (P_i), which corresponds to the limit between the pseudo-elastic behaviour and the plastic state. This creep pressure is determined by the slope break of the creep curve giving $V_{60}-V_{30}$ as a function of p (Curve 2, Fig. 2) [7].

$$E_M = 2(1 + \nu)[V_s + \left(\frac{V_1 + V_2}{2}\right)] \frac{(P_2 - P_1)}{(V_2 - V_1)} \quad (1)$$

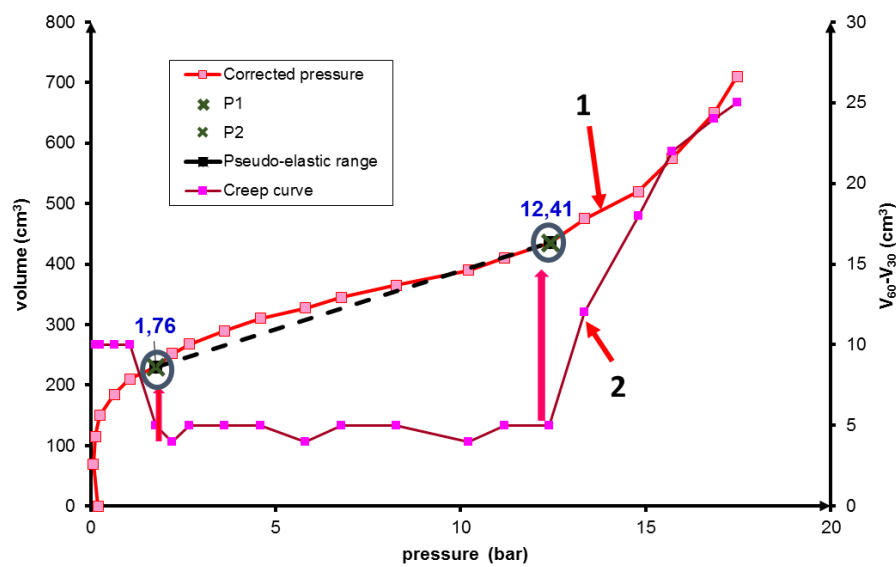


Fig. 2 - Example of a pressuremeter test results, [15]

Analysis of Fig. 2 reveals three distinct phases of the pressuremeter test. The first phase corresponds to the re-establishment of contact between the probe and the borehole wall, ensuring proper load transfer. In the second phase, the rock mass undergoes progressive destructuring, with the deformation curve approaching a linear trend. This linear segment enables the determination of the Ménard pressuremeter modulus, calculated within a defined pressure interval (p_1 to p_2), where p_1 approximates the in-situ horizontal earth pressure (σ_{h0}) and p_2 coincides with the creep pressure (p_i). Beyond the creep threshold, the curve rapidly approaches an asymptote, marking the ultimate limit pressure (p_l), which characterizes the soil's shear failure. This behavior provides critical insights into the mechanical response and strength parameters of the tested formation.

2.2 Overview of artificial neuron networks (ANNs)

The application of neural networks in geo-engineering has developed considerably in recent years, particularly for the prediction of soil mechanical properties [16 – 20]. An artificial neural network is a very simple mathematical operator that aims at approximating arbitrary non-linear functions [21, 22]. Its basic principle is based on learning, which approaches a phenomenon from pairs of inputs/outputs measured or recorded on a system [23 – 26].

Multi-layer Perceptron Neural Network (MLP) is one of the most effective artificial neural network techniques for modeling and prediction, thus it has been used as the benchmark model by many researches [27 – 29]. The MLP has a high capability of universal approximation such that it has been extensively used for modeling nonlinear and complex processes of the real world [30, 31].

In this study, the MLP is employed to analyze and predict the pressuremeter parameters. Basically, the MLP is characterized by a very particular structure: its neurons are organized in successive layers where the information circulates in one direction only, from the input layer to the output layer; it is therefore a direct propagation (feedforward). The neurons of the same layer are not interconnected. A neuron can only send its result to a neuron located in a later layer. The value of the output results from the calculation of the sum of the inputs, weighted by so-called synaptic weight coefficients. A bias (0 or 1) is added to the sum of the weighted inputs to produce an intermediate result modulated by a transfer function, then transmitted to the neurons of the output layer. Fig. 3 provides a schematic diagram of its operation.

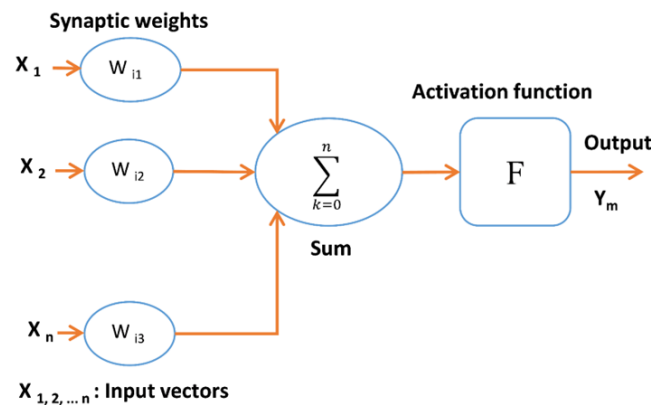


Fig. 3 - Non-linear neuron model [29]

2.3 Geotechnical and environmental context of the study area

The study area encompasses a 170 km electrified double-track railway line connecting Bordj Bou Arreridj to Boumerdès via Bouira in north-central Algeria, traversing complex mountainous terrain that necessitates extensive tunneling, viaduct construction, and large-scale excavations. Geologically, the alignment crosses both external and internal zones of the Maghrebides fold-and-thrust belt, encountering Cretaceous marls, limestones, marly limestones, and argillites (Fig. 4).



Fig. 4 - Geological sets crossed by the railway project line [32]

Located at the active Africa-Eurasia convergent boundary (convergence rate ~ 6 mm/yr), the region exhibits significant tectonic stress manifesting as folds, fractures, and seismic activity in Miocene-Quaternary deposits. The route transects zones of high-to-medium seismicity (Bibans Mountains, Soummam Valley, and Bouira-Thenia corridor), with historical seismic events like the 2003 Boumerdès earthquake (Mw 6.8) causing localized rockfalls but no direct surface ruptures along the alignment (Fig. 5). Hydrogeological conditions feature both continuous alluvial aquifers (with strong river-aquifer connectivity) and discontinuous fractured/karsic aquifers in Cretaceous formations (Fig. 6), requiring comprehensive groundwater management during construction.

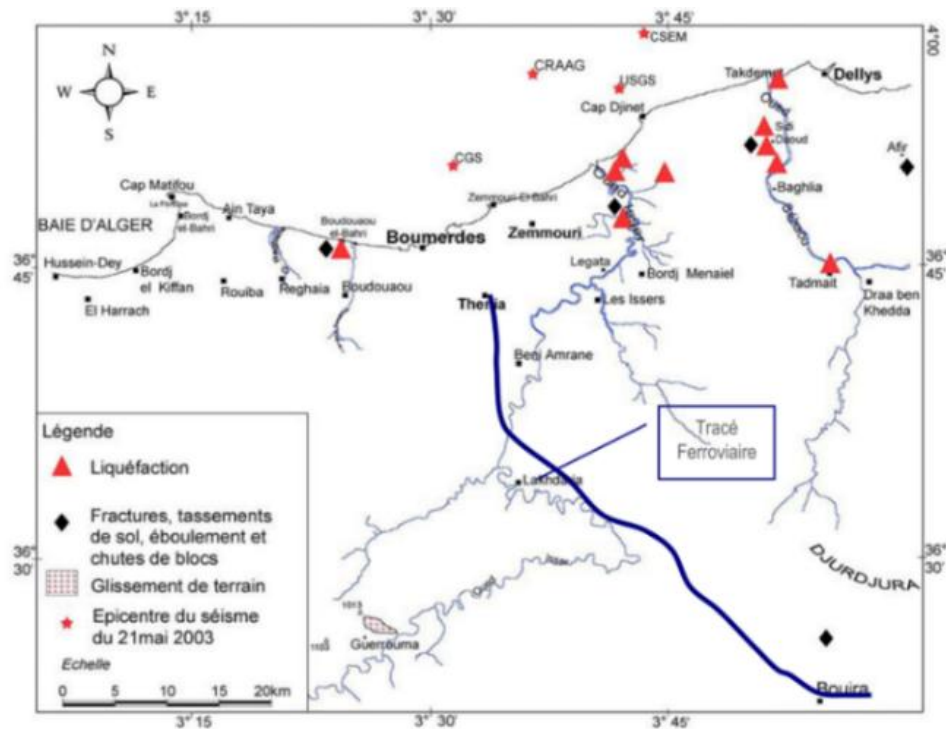


Fig. 5 - Distribution map of the geological effects induced by the Boumerdès earthquake [32]

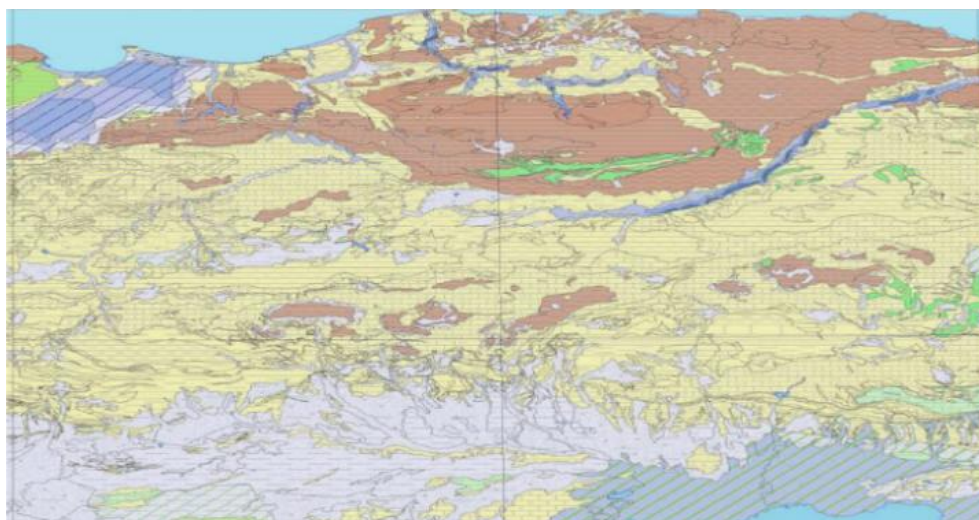


Fig. 6 - Extract from the hydrogeological map of Northern Algeria [32]

3 Methodology and data used

This study includes a multiple regression method and an artificial neural network. First, a simple regression analysis was used to reveal the existence of significant linear or non-linear relationships between the input parameters (e_0 , w_0 , z , S_r , ρ_d , ρ_s) and the output parameters (E_m , P_f , P_i). Then, models linking the pressuremeter modulus (E_m), the limit pressure (P_i) and the creep pressure (P_f) to physical parameters such as depth (z), void ratio (e_0), natural water content (w_0), degree of saturation (S_r), dry density (ρ_d), solid gains density (ρ_s) and bulk density (ρ_h), were developed by the multiple regression method.

This method is always accompanied by an analysis of variance spreadsheet. This spreadsheet allows to test the set of explanatory variables and to infer the variance around the regression equation. In this study, the calculations were performed using Microsoft Excel spreadsheet software. A python-based program was developed to obtain the ANNs. The topology and hyper parameters of the neural network was obtained by the Grid search technique which allowed to test a series of parameters and to compare the performances to deduce the best parameterization.

A database of 120 measurements on different soils was also used: grey hard marl (GHM1), plastic clay (PC), grey sandy clay (GSC1), grey compact marl (GCM), grey silty sand (GSS), grey sandy clay (GSC2), silty sand (SS), alluvial deposit consisting of sand gravel and pebble (ADSGP1), grey hard marl (GHM2), low plastic sandy loam (LPSL1), alluvial deposits containing sand gravel and pebble (ADSGP2), sandy clay (SC), marl clay (MC), low plastic loam (LPL) and low plastic sandy loam (LPSL2). Table 1. summarizes the ranges of variation and average values of the parameters.

Table 1 - Variation and average values of the soil properties studied

Parameters	Variation	Medium
z (m)	[1 - 40]	11.9625
w_0 (%)	[6.25 - 47.2]	16.5168
S_r (%)	[25 - 125.37]	83.6974
ρ_s (Kg/m ³)	[2530 - 2840]	2668.442
ρ_h (Kg/m ³)	[1710 - 2440]	2090.817
e_0 (-)	[0.147 - 1.295]	0.5930
ρ_d (Kg/m ³)	[1220 - 2300]	1783.145
E_m (MPa)	[0.12 - 120.26]	29.4751
P_i (MPa)	[0.08 - 4.664]	1.8678
P_f (MPa)	[0.056 - 3.167]	1.0860

4 Results and discussion

4.1 Simple regression analysis

A simple regression analysis was performed to assess the regression quality and the consistency between the model and the observed data. As a result, the regression equation provides an indication of the suitability of the regression equation to describe the distribution of points. This step is intended to reduce the risk of a local minimum. Table 2. lists the equations.

The correlation is representative for the physical parameters depth (z), void ratio (e_0), natural water content (w_0), dry density (ρ_d) and solid gains density (ρ_s) with the pressuremeter modulus (E_m) and the limit pressure (P_i). The degree of saturation (S_r) was less than 0.15. This means that the mathematical model used does not explain the point distribution. For the creep pressure (P_f), only two parameters exceeded 20% (depth (z) and void ratio (e_0)). The other parameters are not suitable for describing the point distribution.

Table 2 - The equations of the pressuremeter parameters according to e_0 , w_0 , z , S_r , ρ_d and ρ_s

Output(Y)	Input (x)	Simple regression equations	R ²
E_m (MPa)	e_0 (-)	$E_m = -26.63 \ln(e_0) + 10.931$	0.368
	w_0 (-)	$E_m = 52.322e^{-0.072 w_0}$	0.231
	z (m)	$E_m = 2.0185 z + 5.3289$	0.470
	S_r (%)	$E_m = 0.361 S_r - 0.7435$	0.143
	ρ_d (Kg/m ³)	$E_m = 0.0559 \rho_d - 70.182$	0.338
	ρ_s (Kg/m ³)	$E_m = 2E+81 \rho_s^{-23.35}$	0.363
P_l (MPa)	e_0 (-)	$P_l = -1.209 \ln(e_0) + 1.026$	0.402
	w_0 (-)	$P_l = -1.223 \ln(w_0) + 5.1239$	0.284
	z (m)	$P_l = 0.0758 z + 0.9605$	0.352
	S_r (%)	$P_l = 0.0125 S_r + 0.8252$	0.090
	ρ_d (Kg/m ³)	$P_l = 0.0026 \rho_d - 2.8114$	0.395
	ρ_s (Kg/m ³)	$P_l = -17.82 \ln(\rho_s) + 142.47$	0.284
P_f (MPa)	e_0 (-)	$P_f = -0.454 \ln(e_0) + 0.7695$	0.168
	w_0 (-)	$P_f = 5.2447 w_0^{-0.692}$	0.198
	z (m)	$P_f = 0.0364 z + 0.6509$	0.240
	S_r (%)	$P_f = 0.0026 S_r + 0.8675$	0.012
	ρ_d (Kg/m ³)	$P_f = 0.001 \rho_d - 0.6728$	0.165
	ρ_s (Kg/m ³)	$P_f = -6.839 \ln(\rho_s) + 55.036$	0.124

4.2 Multiple regression (MR) analysis

The variables introduced in the proposed regression model are those that increase the coefficient of determination. The data set used represents 105 observations with seven independent variables. The choice of model was based on the square root mean square error (RMSE). Table 3 summarizes the results obtained.

Table 3 - Multiple regression analysis

Multiple regression analysis			
Statistical indicator	E_m	P_l	P_f
R correlation	0.767	0.753	0.616
R ²	0.588	0.567	0.379
R ² adjustment	0.563	0.540	0.341
Standard error	18.383	0.819	0.570
Observations	105	105	105

According to Table 3, the P_f model provided a coefficient of determination (R^2) equal to 0.379, meaning that the regression model accounts for only 37.9% of all variability in the data set. This low value can indicate the presence of a large number of variables that do not have a significant influence (Table 2.). The E_m and P_l model reported a value close to 60%, but this does not indicate that the model is valid for null hypotheses. Therefore, additional tests such as the significance test of the model coefficients have to be considered. This test is performed by the analysis of variance.

The calculated value of F was compared with a theoretical value $F_{(\alpha)}$ obtained from the Fisher tables for a given level of significance $\alpha=0.01$ and for two degrees of freedom k_1 and k_2 . If the value of $F \geq F_{(\alpha)}$, the null hypothesis is automatically discarded which then gives regression coefficients significantly different from zero. Otherwise, the model is not significant and therefore it is not valid.

For all three models E_m , P_l and P_f , the values of F are higher than the critical F value which equals 2.06 with a significance level equal to $\alpha=0.01$. It is noted that the closer the significance level is to 0, the null hypothesis will be rejected. According to the ANOVA results (Table 4.), significance F is well below 0 for all three models. Therefore, for each model at least one of the coefficients is statistically significant at the confidence level and makes a contribution to the model as a whole. Eqs. 2, 3 and 4 were used to obtain the multiple regression models.

$$E_m = 1.55 \times z - 2.72 \times w_0 + 0.68 \times S_r - 0.09 \times \rho_s - 0.022 \times \rho_h + 52.97 \times e_0 - 0.022 \times \rho_d + 288.42 \quad (2)$$

$$P_l = 0.05 \times z - 0.15 \times w_0 + 0.03 \times S_r - 0.004 \times \rho_s - 0.001 \times \rho_h + 2.89 \times e_0 - 0.001 \times \rho_d + 13.65 \quad (3)$$

$$P_f = 0.03 \times z - 0.09 \times w_0 + 0.018 \times S_r - 0.002 \times \rho_s - 0.0005 \times \rho_h + 1.92 \times e_0 - 0.001 \times \rho_d + 8.90 \quad (4)$$

Table 4 - Analysis of variance (ANOVA)

The pressuremeter parameters		Coefficients	Standard Error	t Stat	P-value	F calculation	F($\alpha=0.01$) theoretical
E_m (MPa)	Constant	288.4181	103.5160	2.7862	0.0063	22.8713	5.39E-19
	z	1.5504	0.2343	6.6166	1.31E-09		
	w_0	-2.7246	1.0772	-2.5293	0.0128		
	S_r	0.6845	0.3248	2.1078	0.0373		
	ρ_s	-0.0880	0.0289	-3.0425	0.0029		
	ρ_h	-0.0224	0.0297	-0.7551	0.4518		
	e_0	52.9745	26.4951	1.9994	0.0480		
	ρ_d	-0.0221	0.0264	-0.8385	0.4036		
P_l (MPa)	Constant	13.6512	4.6119	2.9600	0.0038	20.9410	8.53E-18
	z	0.0492	0.0104	4.7110	7.13E-06		
	w_0	-0.1472	0.0480	-3.0674	0.0027		
	S_r	0.0327	0.0145	2.2587	0.0258		
	ρ_s	-0.0041	0.0013	-3.1903	0.0018		
	ρ_h	-0.0010	0.0013	-0.7484	0.4558		
	e_0	2.8858	1.1804	2.4447	0.0161		
	ρ_d	-0.0008	0.0012	-0.6414	0.5226		
P_f (MPa)	Constant	8.9026	3.2092	2.7741	0.0065	9.7864	1.80E-09
	z	0.0304	0.0073	4.185262	5.69E-05		
	w_0	-0.0910	0.0334	-2.72364	0.0075		
	S_r	0.0178	0.0101	1.765734	0.0802		
	ρ_s	-0.0025	0.0009	-2.78134	0.0064		
	ρ_h	-0.0005	0.0009	-0.54018	0.5901		
	e_0	1.9224	0.8214	2.340382	0.0210		
	ρ_d	-0.0009	0.0008	-1.10395	0.2720		

4.3 Artificial Neuron Networks (ANNs) analysis

The program of this study was carried out in a Python environment. The latter is a very powerful calculation software, with libraries designed to create, train and simulate neural networks. The Keras module was used to develop the neuron layers, cost functions, optimizers, activation functions and regulation mechanisms. The data set used for the development of the ANNs models was divided into two parts: one set for learning (105 measurements) and one set for testing (15 measurements).

Next, a normalization of each input and target vector was performed. This data processing was performed using the “sklearn preprocessing” module. The network chosen for this study is a multilayer perceptron feed-forward with an adaptive optimization algorithm “Adam”. This algorithm calculates individual learning rates for different parameters and is specifically designed for the training of deep neural networks.

The Grid search function was used to adjust the model parameters and obtain optimal performance. This function varies the number of neurons and the transfer functions in the hidden layers (Log-sigmoid, sigmoid tangent and linear functions) to optimize and refine the model to be retained. A dropout layer was added to avoid overlearning, which consists in randomly deactivating a certain proportion when learning the model. After several runs, the neural networks proposed were four-layer networks: an input layer composed of eight neurons (corresponding to the soil type, depth (z), void ratio (e_0), natural water content (w_0), degree of saturation (S_r), dry density (ρ_d), bulk density (ρ_h) and solid gains density (ρ_s)), two hidden layers and an output layer (Fig. 3). Table 5. gives the parameterization settings.

Table 5 - Mean absolute test and validation errors for each algorithm

Output	Input	Network architecture	Algorithm	Batch	Iteration	Probability Dropout	Test	
							R ²	RMSE
E_m (MPa)	The soil type, z , w_0 , S_r , ρ_s , ρ_h , e_0 , ρ_d .	8-50-50-1	Adam	10	1000	0.3	0.9934	2.7211
P_l (MPa)	The soil type, z , w_0 , S_r , ρ_s , ρ_h , e_0 , ρ_d .	8-100-100-1	Adam	20	500	0.4	0.9829	0.1762
P_f (MPa)	The soil type, z , w_0 , S_r , ρ_s , ρ_h , e_0 , ρ_d .	8-100-50-1	Adam	20	500	0.2	0.9354	0.2020

Performance was evaluated using the square root mean square error (RMSE) and the coefficient of determination (R^2). Figs. 7(a), 8(a) and 9(a) represent a comparison of the performances of the network developed in this study with the test database. A perfect alignment of the results simulated by the E_m and P_l network around the 45° line is observed (Figures. 7(b) and 8(b)). This finding is confirmed by coefficients of determination (R^2) close to unity, except in the case of the P_f model; a certain dispersion of the data can be noted (Fig. 9(b)). This is probably due to the use of parameters that do not influence the creep pressure. The comparison of the estimated results by the neural network and the measured results allow to conclude on the reliability of the model and its predictive capacity.

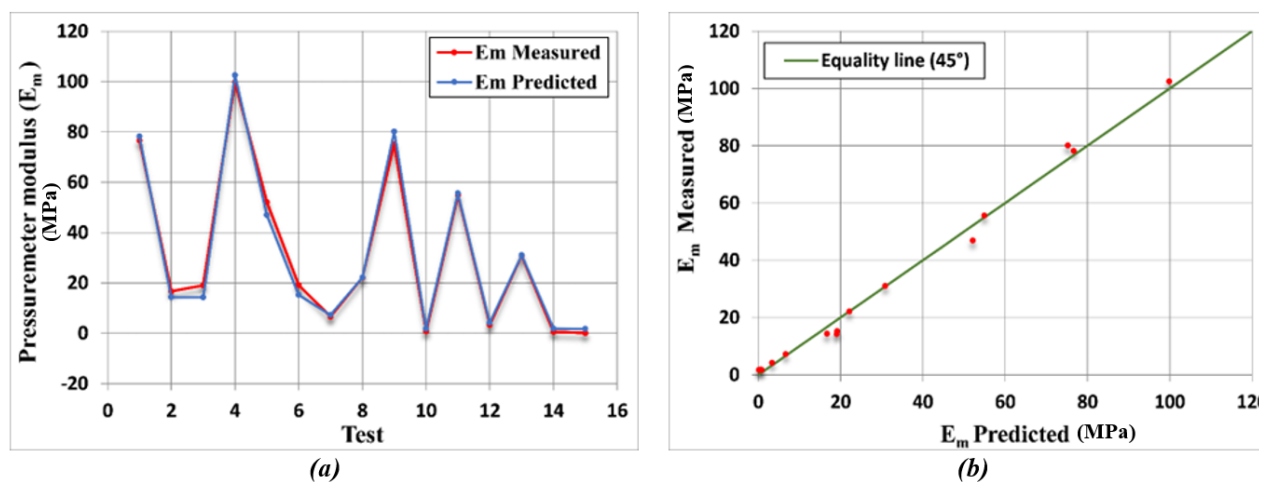


Fig. 7 - (a) Comparison between measured and predicted values by ANNs, (b) Performance of the E_m model

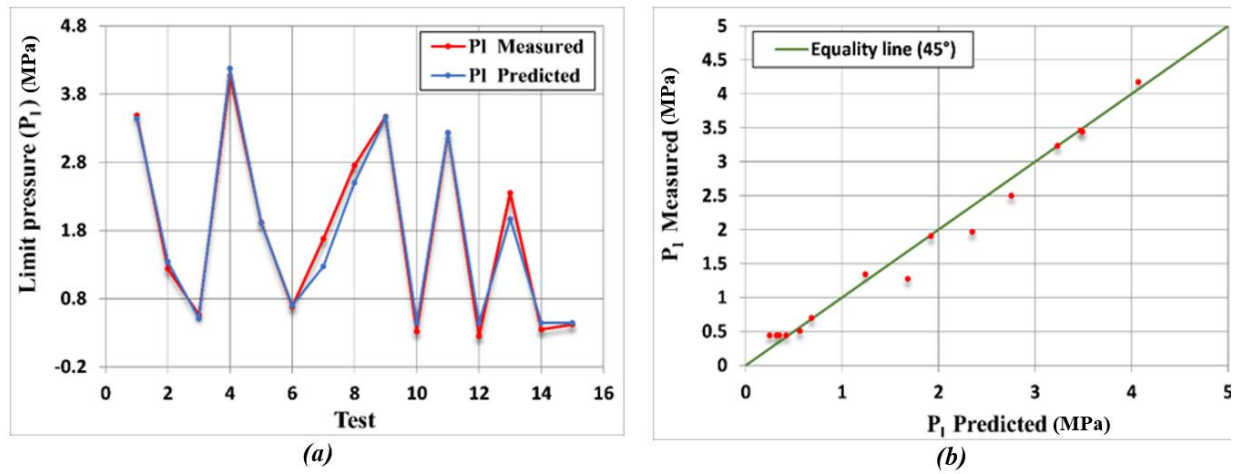


Fig. 8 - (a) Comparison between measured and predicted ANNs values, (b) Performance of the P_l model

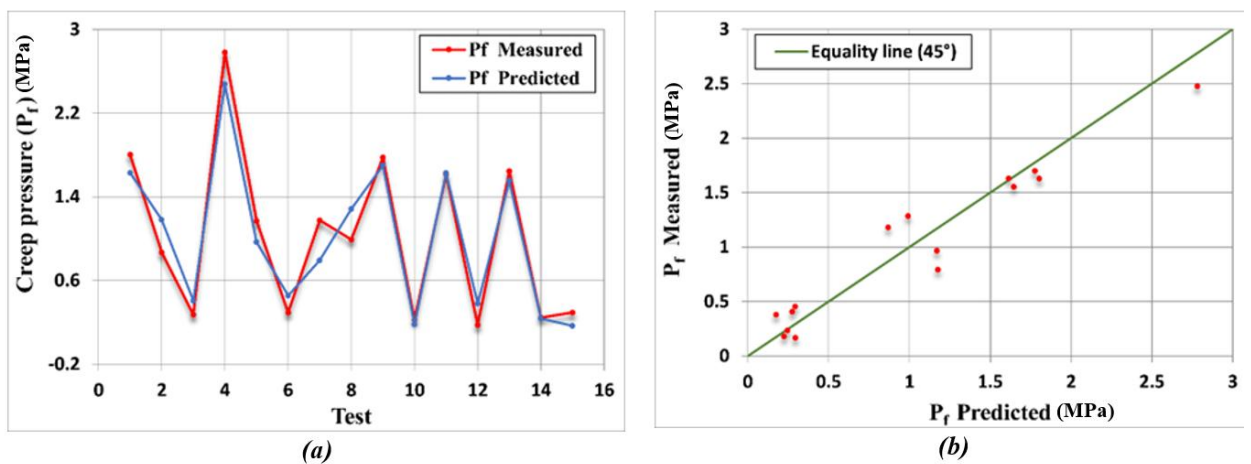


Fig. 9 - (a) Comparison between measured and predicted ANNs values, (b) Performance of the P_f model

5 Comparison of results

The RMSE parameter and the coefficient of determination were examined to evaluate the performance of the multiple regression model and the ANNs model simultaneously. Table 6. summarizes the performance of the two models used for prediction. The study also indicates that the ANNs analysis gives more accurate results for the prediction of the pressuremeter modulus E_m . The neural network gave an error seven times smaller than that of multiple regression. This proves that the topology of two hidden layers and the number of neurons adopted is an optimal choice.

Prediction of the limit pressure P_l with influential parameters and a sufficient number of input variables in the ANNs models provided predictive reliability in contrast to multiple regression (Table 7.). Indeed, similar studies have shown that the more inputs are increased, the better performance the model can reproduce. An example is the study carried out by [33 – 37]. For the prediction of the creep pressure P_f , the comparison of the results estimated by the neural networks with the multiple regression allows to conclude on the reliability of the model and its predictive power (Table 8.).

Table 6 - Comparison between the neural network model and the multiple regression model for Em

Soil type	z (m)	w (%)	S_r (%)	ρ_s (Kg/m³)	ρ_h (Kg/m³)	e₀ (-)	ρ_d (Kg/m³)	Measured	RM E_m (MPa)	RNA
GHM1	32	9.39	118.4	2606	2400	0.206	2190	76.6430	72.7865	78.2359
PC	6	10.2	38.6	2675	1900	0.706	1550	16.7000	21.4127	14.3714
GSC1	2	10.56	97.98	2580	2280	0.278	2060	19.0370	20.7754	14.2679
GCM	22	8.95	112.92	2530	2390	0.200	2190	99.8460	61.3271	102.561
GSS	9	28	96.85	2660	1969	0.769	1526.36	52.1000	21.0754	46.9637
GSC2	4	10.56	97.98	2580	2280	0.278	2060	19.1660	23.8762	15.2572
SS	10	8.9	36	2826	1750	0.698	1640	6.6400	17.0303	7.24659
ADSGP1	6	11.27	84.85	2580	2190	0.342	1960	22.1120	23.6730	22.1858
GHM2	36	9.39	118.4	2606	2400	0.206	2190	75.2440	78.9880	80.1913
LPSL1	8.5	21.1	88.5	2840	2050	0.680	1690	0.8300	7.3879	1.76535
ADSGP2	22	10.17	102.85	2580	2310	0.255	2100	54.9280	53.4044	55.6441
SC	14	23.2	72.6	2655	1970	0.848	1590	3.3300	28.4994	4.20505
MC	12	26.3	94	2655	1950	0.742	1540	30.8500	27.5394	31.0779
LPL	11.5	47.2	100	2790	1790	1.295	1220	0.5900	1.9981	1.84979
LPSC2	7.5	21.1	88.5	2840	2050	0.680	1690	0.1300	5.8375	1.77003
The square root of the mean square error (RMSE)									14.9606	2.7211
Coefficient of determination (R²)									0.7888	0.9934

Table 7 - Comparison between the neural network model and the multiple regression model for PI

[illegible]

Table 8 - Comparison between the neural network model and the multiple regression model for Pf

Soil type	z (m)	w (%)	S _r (%)	ρ_s (Kg/m ³)	ρ_h (Kg/m ³)	e ₀ (-)	ρ_d (Kg/m ³)	Measured	RM	RNA
								P _f (MPa)		
GHM1	32	9.39	118.4	2606	2400	0.206	2190	1.8030	1.8514	1.6293
PC	6	10.2	38.6	2675	1900	0.706	1550	0.8680	1.1837	1.1808
GSC1	2	10.56	97.98	2580	2280	0.278	2060	0.2740	0.8501	0.4063
GCM	22	8.95	112.92	2530	2390	0.200	2190	2.7810	1.6730	2.4770
GSS	9	28	96.85	2660	1969	0.769	1526.36	1.1700	0.8371	0.9670
GSC2	4	10.56	97.98	2580	2280	0.278	2060	0.2930	0.9109	0.4541
SS	10	8.9	36	2826	1750	0.698	1640	1.1760	0.9785	0.7936
ADSGP1	6	11.27	84.85	2580	2190	0.342	1960	0.9910	0.9317	1.2855
GHM2	36	9.39	118.4	2606	2400	0.206	2190	1.7760	1.9730	1.7005
LPSL1	8.5	21.1	88.5	2840	2050	0.680	1690	0.2240	0.4928	0.1804
ADSGP2	22	10.17	102.85	2580	2310	0.255	2100	1.6140	1.4850	1.6294
SC	14	23.2	72.6	2655	1970	0.848	1590	0.1750	1.1009	0.3790
MC	12	26.3	94	2655	1950	0.742	1540	1.6450	0.9899	1.5532
LPL	11.5	47.2	100	2790	1790	1.295	1220	0.2450	0.2749	0.2357
LPSC2	7.5	21.1	88.5	2840	2050	0.680	1690	0.2940	0.4624	0.1670
The square root of the mean square error (RMSE)									0.4926	0.2020
Coefficient of determination (R ²)									0.6038	0.9354

6 Conclusion

This study presents a comparative analysis of multiple regression and artificial neural network (ANN) approaches for predicting pressuremeter parameters from conventional laboratory soil properties (soil type, depth, void ratio, water content, density parameters). The ANN model demonstrated superior predictive performance, achieving a coefficient of determination $R^2 > 0.93$ and low RMSE values, indicating excellent agreement with experimental pressuremeter data. While the ANN's black-box nature limits explicit interpretation of parameter influences, its computational advantage in handling complex nonlinear soil behavior makes it particularly valuable for practical geotechnical applications. The multiple regression method provided complementary benefits through transparent parametric relationships expressed in equation form. For optimal engineering applications, we recommend: (1) expanding the training database to enhance model generalizability across diverse soil conditions, (2) incorporating additional geotechnical parameters to better capture spatial variability, and (3) developing hybrid modeling approaches that combine the predictive power of ANNs with the interpretability of regression analysis. These improvements would significantly advance the reliability of pressuremeter parameter estimation for critical geotechnical design applications, particularly in foundation engineering where accurate soil characterization is paramount.

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