COMPARING NONLINEAR REGRESSION ANALYSIS AND ARTIFICIAL NEURAL NETWORKS TO PREDICT GEOTECHNICAL PARAMETERS FROM STANDARD PENETRATION TEST

Mohammed Amin BENBOURAS
PhD student, Civil Engineering Department, University of Abbes Laghrour, Khenchla, Algeria, e-mail: mouhamed_amine.benbouras@g.enp.edu.dz

Ratiba MITICHE KETTAB
Professor, Civil Engineering Department, National Polytechnic School, Algiers, Algeria, e-mail: ratiba.kettab@g.enp.edu.dz

Hamma ZEDIRA
Professor, Civil Engineering Department, University of Abbes Laghrour, Khenchla, Algeria, e-mail: zedirahamma2003@yahoo.fr

Fatiha DEBICHE
Assistant Professor, Civil Engineering Department, National Polytechnic School, Algiers, Algeria, e-mail: fatiha.debiche@enp.edu.dz

Narimane ZAIDI
PhD student, Civil Engineering Department, University of Abbes Laghrour, Khenchla, Algeria, e-mail: narimane.zaidi15@gmail.com

Abstract. At the beginning the twenty-first century, a lot of high-level methods have become available in geotechnical engineering in order to deal with the complexity and heterogeneity encountered in soil, Statistical modeling (i.e. regression analysis method) was used to estimate the relationships among two or more variables, however in the early nineties an application of a new system emerged which gave excellent results in solving a lot of problems by learning from the available data so-called ”artificial neural network”. The aim of this study is to apply both methods, nonlinear regression analysis and artificial neural networks in order to predict geotechnical parameters from standard penetration test in all soil's types; Comparison of the results using correlation's coefficient (R) and Root Mean Squared Error (RMSE) is done between both methods; About 400 samples, over 65 boreholes in the Algiers area have been collected and were used in this study, The results show the superiority of ANN method in predicting data that seems closer to experimental values compared to NRA method.

Key words: artificial neural network, regression analysis, standard penetration number and geotechnical parameters.

1. Introduction

Empirical relationships are considered as an important part of the Geotechnical Engineering where it has been used to solve many of the dilemmas, interpretation of several phenomena and estimation of the preliminary unknown value based on other determined factors during the initial geotechnical study (Ameratunga *et al.,* 2016; Dysli *et al.,* 2013); In view of the great importance of this issue, the first section of eurocode 7 (EN 1997-1) published by the European committee for standardization which is a very important, indispensable and has been implemented in all EU countries, it recommends clearly using past experiences and correlations and requests the use of at least two types of correlations (Michel *et al.,* 2013), Moreover regression analysis and Artificial neural network (ANN) are the most commonly used methods adopted for the development of relations between material parameters (Harini *et al.,* 2014).

Regression analysis is a statistical process based on estimating the relationship between two variables or more, it includes many techniques for modeling and analyzing several variables and finally fitting a linear or nonlinear equation, On the other hand Artificial neural networks (ANN) are a form of artificial intelligence which attempt to simulate the human brain behavior and nervous system (Alshayeb et al, 2013), ANN learn from the examples of the data provided to them in order to capture the precise functional relationships between them, even if the underlying relationship is unknown or difficult to explain its physical meaning (Shahin *et al.,* 2001; Raghdan *et al.,* 2013), also studies indicate that due to the development of computer hardware and software, it has been easy to collect databases and become ANN more commonly used and reliable from statistical models, which contributed to their spread in a lot of disciplines because of its specific characteristics to determine the complex systems between the input and output, equally important to identify the appropriate nonlinear equations between them (Al-Saffar *et al.,* 2013).

Many previous studies compared between artificial neuron network to multiple linear regression in geotechnical engineering; for example (Harini *et al.,* 2014) compared between them for prediction of California Bearing Ratio (CBR) of fine grained soils; (Boadu *et al.,* 2013; Siddiqui *et al*l, 2014) have tried to foretell geotechnical parameters from electrical measurements comparing between the two methods; In addition many authors have proven the effectiveness of ANN from statistical models (MLR) using comparison of geotechnical parameters; however, studies that have compared artificial neuron network and nonlinear regression analysis are few and old , The issue that prompted us to compare between ANN and NRA (using 9 nonlinear models) Is looking for better results.

The main objective of this research is to compare the effectiveness of each nonlinear regression analysis method and Artificial neural network using standard penetration number (Nspt) to anticipate some geotechnical parameters (dry density (Yd), wet density (Yh) , plasticity index (Ip), water content (w), void ratio (e); plastic limit (Wp); liquid limit (Wl), consistency index (Ic),fine contents (FC),median grain diameter (D50), cohesion (Cu) and friction angle (□)) ; The comparison was made using both variables the correlation coefficient (R) and Root Mean Squared Error (RMSE) between both methods and in all soil's types; In addition to what has been mentioned The database collected from several geotechnical laboratory encompasses about 400 analyzed samples have been derived from 65 boreholes in the Algiers area.

2. Materials and Methods

2.1 Artificial neural network ANN

2.1.1 Overview of ANN

The human brain is pursuing a complex way to train itself to process information, so a typical neuron collects signals from others neuron through a series of fine structures known as dendrites; the neuron sends out spikes of electrical activity through a long thin stand known as the axon, which is divided into thousands of branches, at the end of each branch, there is a structure called the synapse, which transfer activity from the axon into electrical effects that inhibit or excite the activity, Thus, when the neurons receive exciting inputs that are large enough compared with the inhibitory input, it sends high electrical activity down its axon, and so repeat this process with several neurons that would allow the human brain learning to process information (See Fig. 1) (Shahin *et al.*, 2001, Park, 2011).

The idea of artificial neural network which is a set of neurons known as «processing elements» (PEs), «nodes» or «units», so they are typically arranged in layers: an input layer, an output layer and one or more intermediate layers called hidden layers; Each processing element in a particular layer is wholly or partially relates to many of the PEs in the other layer through Weighted links (Fig. 2) (Shahin *et al.*, 2008; Rakhshandehroo *et al*, 2012).

The consequence of this joined summation is achieved through a transfer function that can also be utilized depending upon the type of problem to be solved by the network (e.g. linear; sigmoidal; Tangent sigmoidal function) (Park, 2011) in order to create the output of the nodes. For PE j (Shahin *et al.*, 2008), this procedure is shown in Equations 1 and 2 and illustrated in Fig. 2.

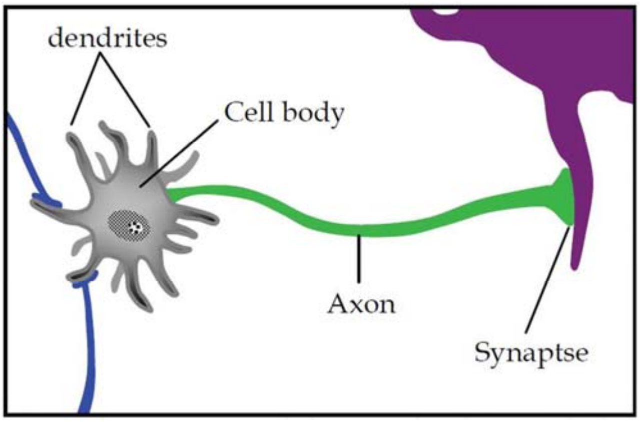


Fig. 1. The functioning of human neurons (Park, 2011).

$$I_j=\sum W_{ji} X_i + \theta_i \quad \text{...............1}$$

$$Y_i=f(I_i) \quad \text{.......................2}$$

A fundamental methodology of Artificial Neural Networks is composed of three stages (i) Network training, (ii) Network testing and (iii) Network validation. "Training" the neural network involves modifying the connected weights by providing repeatedly a historical range of model inputs and corresponding desired outputs. The aim is to reduce errors between the expected and desired output values. And continue the training process using Back Propagation Algorithm in order to achieve some stopping criteria so that the network could get a bundle of weights and bias unit that will produce the smallest possible error (Chok *et al.*, 2016).

2.1.2 ANN Architecture

The design of the network structure is one of the most important and difficult quests in the development of ANN model. It must choose the optimum number of layers and the number of branches in each one. There is no standard approach to determine the optimal ANN structure, but nevertheless a lot of studies have tried to develop rules to enable effective network design.

2.1.2.1 Number of Layers:

Studies varied in determining the number of hidden layers, where (Cybenko, 1989; Hornik *et al.*, 1989) demonstrated that a single hidden layer is enough to approximate any continuous function, provided the use of the sufficient weights; (Flood and Kartam, 1994; Ripley, 1996; Sarle, 1994) stated that the use of more than one hidden layer offers the necessary flexibility for modeling complex functions in many cases, (Lapedes and Farber, 1988) Provided more evidence realistic that two hidden layers are sufficient; As explained by (Chester, 1990) it is being used the first hidden layer for extracting local characteristics of the input patterns while the second hidden layer is helpful for extracting global features of the training patterns (Shahin *et al.*, 2008).

2.1.2.2 Number of Nodes:

The number of nodes in the input and output layers are limited by the number of inputs and outputs specified in the network, respectively. There is no direct and accurate way to determine the best number of nodes in each hidden layer, but there are some formulas proposed by the researchers summarized in Table 1.

2.2. Sampling and Testing

Soil samples were performed through the various geological formations in different areas of Algiers using geological maps as a guide. Overall, 394 samples have been obtained from the 68 boreholes, where their depth ranges between 10 to 103 m with an average of 45.7 m, The data were collected from a number of projects which have been implemented in Algiers from several geotechnical laboratories, In the current study it has been divided, according to the soil's kind into five types (clay, sand, marl, silt and gravel), as Fig. 3 represents a map of collected boreholes from the study area site. Geotechnical parameters that were collected for this study, were set in the laboratory according to European standards; moisture content using (norm EN-NF P 94-049-2, 1996); Atterberg limits by utilizing (EN-NF P94-051, 1993); dry and wet density according to (EN-NF P94-061-2, 1996); Shear strength using (EN-NF P94-071, 1994) ; particle size analysis (EN-NF P94-056, 1996); finally SPT test depending (EN-NF P94-116, 1991).

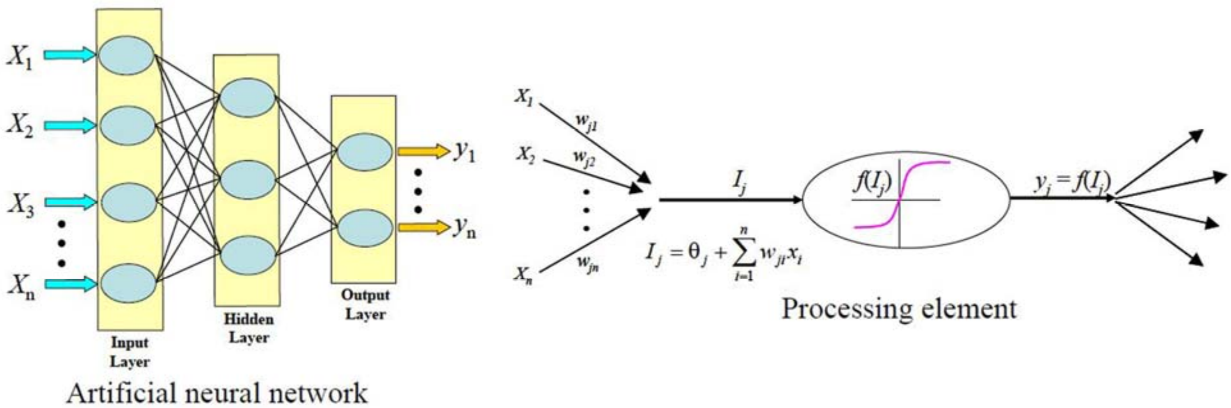


Fig. 2. A model structure and modus operandi of Artificial Neural Networks (Shahin *et al.*, 2008)

Table 1. The proposed formulas in the literatures to approximate nodes' number (Park, 2011; Smith, 1986).

No	*Equation*	*Equation's number*	*Reference*
1	H=2i+1	(3)	Hecht–Nielsen, 1987; Caudill, 1988)
2	H=i-1	(4)	Yu, 1992
3	$H = \frac{i+o}{2}$	(5)	Yeh,1997a
4	$H = \sqrt{i \times o}$	(6)	Yeh, 1997b
5	H=2i	(7)	Kanellopoulos and Wilkinson, 1997
6	$H = \frac{t-o}{i+o+1}$	(8)	Najjar, 1999

Table 2. Nonlinear regression analysis models using in this study

Models	*Curve Fitting*	*Equation's number*
EXP Degree1	$f(x) = a \times exp^{bx}$	(9)
EXP Degree2	$f(x) = a \times exp^{bx} + c \times exp^{dx}$	(10)
Linear	$f(x) = ax + b$	(11)
Poly Degree2	$f(x) = ax^2 + bx + c$	(12)
Poly Degree3	$f(x) = a1x^3 + a2x^2 + a3x + a4$	(13)
Power term1	$f(x) = ax^b$	(14)
Power term2	$f(x) = ax^b + c$	(15)
Fourier term1	$f(x) = a0 + a1 \times cos(wx) + b1 \times sin(wx)$	(16)
ANN	Back Propagation Algorithm	

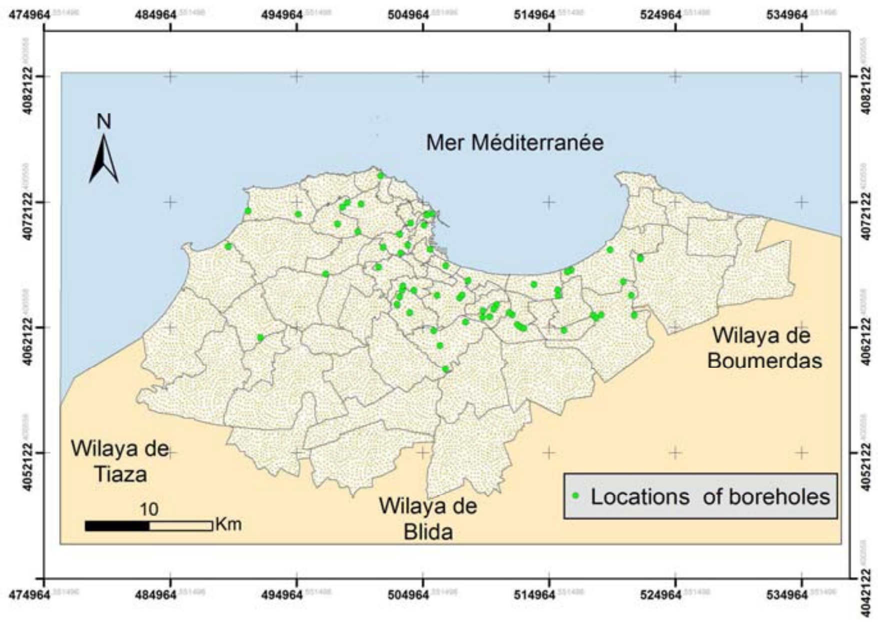


Fig. 3. Map of boreholes location in the studied area site.

2.3. Methodology

In order to search for a relationship between Nspt and various geotechnical parameters, also comparing the effectiveness of the relationship using each of these methods (nonlinear regression analysis and Artificial neuron neural network); the following methodology has been adopted:

- Collecting information about the Algiers' soil, from various geotechnical laboratories, especially sounding related to SPT test.
- Processing information using both methods (NRA and ANN), MATLAB software has been utilized according to its effectiveness and flexibility that have been observed during previous

research (Khattab *et al.*, 2003); More particularly the use of the neural fitting application to apply ANN method and the curve fitting tool to stratify NRA; noting that both applications belong to MATLAB program.

- Regarding the network design in the ANN method; two hidden layers have been used, so as to impart flexibility and efficiency on the network (Shahin *et al.*, 2008), and to calculate the number of nodes in the first layer in which was applied formula proposed by (Najjar, 1999) (see Table 1).
- For more effectiveness and to obtain relevant results when nonlinear regression analysis method could be compared with ANN method, it has been selected several non-linear models in order to be applied on the bilateral (input-output), as follows (EXP Degree1, EXP Degree2, Linear, Poly Degree2, Poly Degree3, Power term1, Power term2, Fourier term1, rational term2) as it has been highlighted in Table 2.
- The correlation's coefficient R, and the root mean squared error (RMSE) are the basic criteria that are often used to assess the performance prediction, where the correlation coefficient is a key measure used to determine the relative relationship between the expected and observed data (Shahin *et al.*, 2008). Smith (1986) proposed the following guide to assess R:

-|R|≥ 0.8 strong correlation.
-0:2 < |R| < 0.8 correlation exists.
-And |R| ≤ 0.2weak correlation.

3. Results and discussion

3.1. Empirical correlation using both methods ANN and NRA (relationship between Nspt and Cu as an example)

In order to illustrate the use of both methods in the following methodology we will shed light on one example showing the correlation between Nspt and Cu for the gravel type, where the use of curve fitting tool in MATLAB software utilizing nine nonlinear models proves that the Fourier model is the most appropriate to correlate the two variables with correlation' coefficient R=0.65 and RMSE=0.411, the results of correlation between the two variable using curve fitting tools, the equation of correlation and the fitting graph are shown in Fig. 4; In the other hand the use of ANN to correlate Nspt with Cu for gravel as an example to compare both methods using the neural fitting application in MATLAB software give an excellent result.

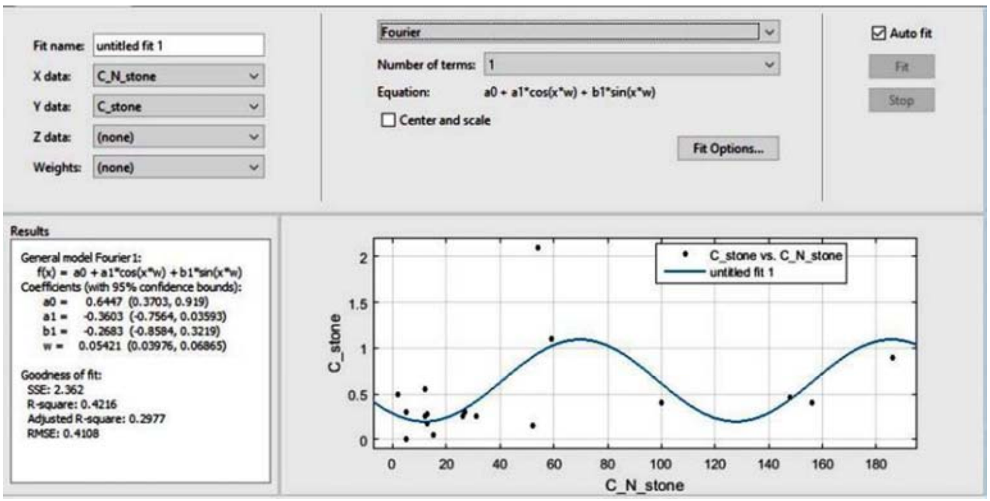


Fig. 4. Correlation between Nspt and Cu in the gravel using Fourier nonlinear model.

Table 3. Matrix of correlation between N and other geotechnical parameters.

		EXP Deg1		EXP Deg2		Poly Deg1		Poly Deg2		Poly Deg3		Power		Power		Fourier		ANN	
		R	RMS	R	RMS	R	RMS	R	RMS	R	RMS	R	RMSE	R	RMSE	R	RMSE	R	RMS
Yd	clay	0.40	0.118	0.46	0.119	0.41	0.117	0.47	0.116	0.47	0.118	0.33	0.122	0.46	0.116	0.18	0.131	0.76	0.080
	sand	0.04	0.159	0.23	0.178	0.04	0.159	0.10	0.169	0.60	0.147	0.09	0.158	0.52	0.145	0.95	0.059	0.76	0.088
	marl	0.36	0.155	0.38	0.156	0.36	0.155	0.39	0.155	0.39	0.156	0.35	0.156	0.37	0.156	0.17	0.167	0.57	0.136
	silt	0.31	0.125	0.24	0.153	0.24	0.125	0.24	0.137	0.57	0.129	0.17	0.127	0.24	0.136	0.56	0.130	0.91	0.042
	stone	0.39	0.156	0.64	0.135	0.38	0.157	0.63	0.133	0.64	0.135	0.54	0.143	0.56	0.143	0.63	0.137	0.72	0.113
Yh	clay	0.13	0.239	0.14	0.242	0.13	0.239	0.14	0.240	0.14	0.242	0.14	0.238	0.14	0.240	0.14	0.242	0.43	0.215
	sand	0.11	0.288			0.11	0.288	0.11	0.293	0.24	0.291	0.09	0.289	0.11	0.293	0.45	0.268	0.46	0.263
	marl	0.26	0.145	0.34	0.143	0.27	0.145	0.35	0.142	0.35	0.142	0.30	0.143	0.30	0.144	0.22	0.148	0.58	0.122
	silt	0.53	0.112	0.75	0.107	0.54	0.111	0.68	0.106	0.68	0.118	0.37	0.123	0.68	0.106	0.68	0.118	0.89	0.057
	stone	0.24	0.230	0.35	0.227	0.24	0.231	0.28	0.230	0.41	0.221	0.25	0.230	0.25	0.232	0.29	0.232	0.62	0.184
W	clay	0.22	5.966	0.31	5.914	0.22	5.976	0.31	5.863	0.31	5.913	0.11	6.084	0.28	5.920	0.13	6.178	0.36	5.650
	sand	0.10	8.410	0.37	8.186	0.10	8.412	0.12	8.564	0.12	8.748	0.03	8.447	0.32	8.181	0.17	8.689	0.57	6.710
	marl	0.20	5.161	0.23	5.203	0.20	5.165	0.21	5.186	0.25	5.178	0.19	5.174	0.20	5.197	0.25	5.174	0.52	4.454
	silt	0.65	5.694	0.75	6.105	0.63	5.800	0.69	5.930	0.69	6.611	0.54	6.309	0.69	5.964	0.82	5.262	0.90	2.899
	stone	0.21	7.591	0.31	7.560	0.22	7.575	0.30	7.483	0.32	7.533	0.21	7.588	0.23	7.633	0.17	7.825	0.58	6.310
e	clay	0.36	0.251	0.53	0.244	0.37	0.250	0.42	0.252	0.52	0.245	0.45	0.241	0.47	0.245	0.42	0.260	0.83	0.166
	sand	0.66	0.150	0.99	0.056	0.70	0.141	0.84	0.131	0.87	0.169	0.74	0.133	0.98	0.048	0.84	0.186	0.97	0.098
	marl	0.54	0.137	0.54	0.141	0.53	0.137	0.54	0.139	0.59	0.135	0.48	0.143	0.54	0.139	0.53	0.142	0.70	0.113
	stone	0.20	0.395	0.58	0.387	0.23	0.392	0.65	0.332	0.65	0.363	0.37	0.373	0.54	0.367	0.64	0.366	0.65	0.263
FC	clay	0.08	15.55	0.48	13.95	0.08	15.55	0.08	15.68	0.15	15.69	0.14	15.440	0.48	13.840	0.23	15.45	0.46	13.69
	sand	0.07	32.92	0.37	31.45	0.04	32.96	0.37	31.04	0.37	31.42	0.11	32.790	0.12	33.130	0.25	32.70	0.45	28.78
	marl	0.14	23.79	0.28	23.31	0.15	23.77	0.21	23.63	0.27	23.37	0.09	23.930	0.27	23.300	0.13	24.10	0.47	21.04
	silt	0.02	29.40	0.53	27.02	0.02	29.40	0.49	26.62	0.51	27.56	0.17	28.990	0.28	29.400	0.40	29.31	0.82	16.10
	stone	0.11	33.13	0.34	31.81	0.14	33.03	0.37	31.23	0.37	31.42	0.23	32.450	0.23	32.640	0.38	31.17	0.48	29.07
D50	clay	0.60	0.003	0.60	0.004	0.65	0.003	0.69	0.003	0.71	0.003	0.67	0.003	0.68	0.003	0.71	0.003	0.75	0.003
	sand	0.04	0.204	0.25	0.209	0.06	0.204	0.31	0.199	0.39	0.198	0.14	0.202	0.15	0.207	0.39	0.199	0.69	0.140
	marl	0.25	0.033	0.50	0.035	0.27	0.033	0.29	0.035	0.63	0.031	0.17	0.034	0.29	0.035	0.66	0.030	0.99	0.004
	stone	0.57	0.251	0.59	0.259	0.37	0.286	0.50	0.271	0.55	0.267	0.57	0.253	0.57	0.253	0.50	0.277	0.60	0.239
WL	clay	0.41	10.03	0.43	10.10	0.41	10.02	0.41	10.10	0.43	10.10	0.37	10.220	0.41	10.100	0.43	10.10	0.48	9.706
	sand	0.40	12.51	0.49	12.46	0.38	12.66	0.47	12.30	0.49	12.41	0.26	13.210	0.48	12.230	0.41	13.02	0.56	11.01
	marl	0.19	12.91	0.21	13.04	0.19	12.91	0.19	13.00	0.30	12.72	0.24	12.770	0.25	12.800	0.24	12.95	0.47	11.52
	silt	0.14	7.624	0.66	6.589	0.14	7.618	0.59	6.575	0.64	6.735	0.30	7.329	0.50	7.066	0.37	8.089	0.74	4.892
	stone	0.31	13.76	0.33	13.96	0.31	13.77	0.31	13.89	0.33	13.97	0.22	14.130	0.32	13.880	0.40	13.58	0.61	11.30
WP	clay	0.46	3.988	0.47	4.039	0.46	3.985	0.46	4.019	0.48	4.002	0.40	4.114	0.46	4.019	0.50	3.970	0.64	3.425
	sand	0.77	8.116	0.86	6.722	0.66	9.534	0.85	6.766	0.86	6.728	0.57	10.510	0.86	6.754	0.28	12.76	0.90	5.562
	marl	0.04	7.405	0.08	7.496	0.04	7.405	0.12	7.410	0.30	7.172	0.07	7.393	0.15	7.381	0.26	7.263	0.65	5.582
	silt	0.19	3.385	0.59	3.152	0.20	3.380	0.54	3.074	0.58	3.201	0.34	3.241	0.52	3.122	0.31	3.724	0.69	2.308
	stone	0.15	11.38	0.22	11.49	0.16	11.38	0.19	11.44	0.29	11.27	0.12	11.440	0.16	11.490	0.37	10.94	0.50	9.728
IP	clay	0.29	7.858	0.29	7.994	0.29	7.858	0.29	7.925	0.31	7.942	0.24	7.956	0.29	7.924	0.22	8.143	0.38	7.505
	sand	0.37	7.269	0.54	6.865	0.42	7.088	0.57	6.565	0.57	6.697	0.21	7.653	0.55	6.652	0.31	7.746	0.66	5.660
	marl	0.26	8.925	0.28	9.008	0.25	8.942	0.26	8.973	0.28	9.007	0.27	8.888	0.27	8.948	0.26	9.041	0.35	8.576
	silt	0.09	4.354	0.69	3.572	0.09	4.353	0.62	3.631	0.67	3.669	0.27	4.213	0.47	4.091	0.42	4.489	0.75	2.937
	stone	0.28	9.488	0.49	8.806	0.27	9.530	0.33	9.420	0.36	9.444	0.19	9.719	0.37	9.283	0.37	9.405	0.55	8.294
IC	clay	0.07	0.240	0.31	0.233	0.07	0.240	0.29	0.233	0.30	0.234	0.19	0.236	0.23	0.236	0.29	0.235	0.35	0.221
	sand	1.00	0.675	1.00	0.416	0.88	3.476	1.00	0.710	1.00	0.408	0.99	0.969	1.00	0.419	0.40	7.001	0.99	0.342
	marl	0.17	0.439	0.38	0.419	0.18	0.438	0.29	0.429	0.46	0.402	0.18	0.438	0.19	0.440	0.23	0.440	0.88	0.359
	silt	0.51	0.337	0.68	0.351	0.55	0.326	0.74	0.286	0.79	0.296	0.35	0.366	0.79	0.261	0.67	0.356	0.84	0.184
	stone	0.18	1.104	0.39	1.068	0.21	1.099	0.37	1.059	0.38	1.070	0.31	1.067	0.35	1.069	0.37	1.076	0.50	0.942
Cu	clay	0.04	0.388	0.52	0.351	0.05	0.388	0.54	0.336	0.54	0.346	0.12	0.386	0.29	0.383	0.58	0.336	0.66	0.279
	sand	0.08	23.14	0.26	24.58	0.10	23.10	0.20	23.75	0.28	24.46	0.00	23.230	0.15	23.990	0.23	24.74	0.26	20.93
	marl	0.02	0.492	0.56	0.397	0.01	0.492	0.84	0.307	0.85	0.368	0.35	0.462	0.58	0.463	0.85	0.363	0.81	0.345
	stone	0.26	0.488	0.44	0.485	0.29	0.484	0.40	0.479	0.50	0.467	0.35	0.474	0.35	0.489	0.65	0.411	0.96	0.177
φ	clay	0.55	4.900	0.57	5.125	0.56	4.865	0.58	4.948	0.58	5.084	0.45	5.240	0.58	4.924	0.58	5.111	0.62	4.420
	sand	0.29	8.291	0.58	7.706	0.29	8.288	0.29	8.656	0.54	7.999	0.17	8.533	0.29	8.652	0.49	8.285	0.60	6.398
	marl	0.03	8.042	0.22	10.12	0.03	8.042	0.21	8.789	0.23	10.11	0.08	8.019	0.13	8.918	0.20	10.18	0.39	7.405
	stone	0.40	10.39	0.40	11.05	0.40	10.38	0.40	10.70	0.41	11.03	0.25	10.990	0.41	10.690	0.41	11.00	0.71	7.634

Therefore after 21 epochs where it was found the best result in the fifteenth epoch (Fig. 6) with a mean of RMSE between the train, validation and test data equal 0.177 which relatively represents a small error compared to the first one, as well as a best coefficient of correlation was found approximately R=0.96 in all type of data (train, validation and test) see Fig. 5.

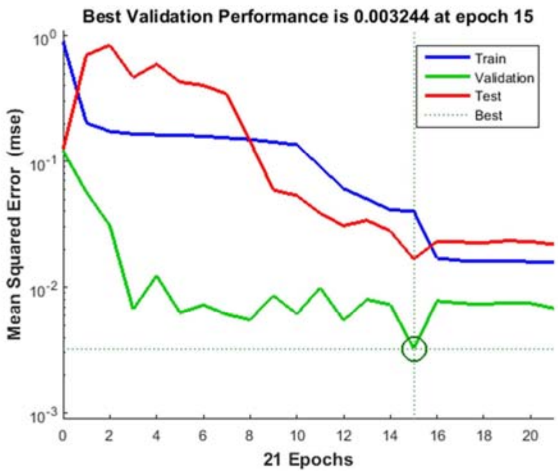


Fig. 5. Variation of mean squared error MSE in different epochs

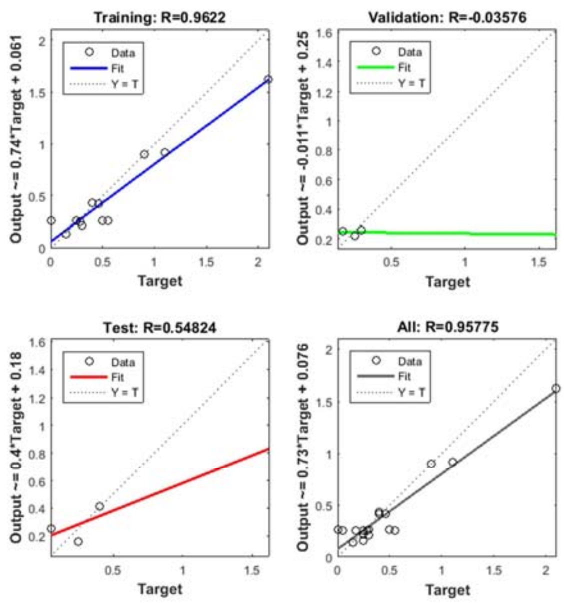


Fig. 6. Correlation between Nspt and Cu in the gravel using ANN.

3.2. Matrix of correlation using artificial neural network (ANN) and nonlinear regression analysis (NRA):

Matrix of correlation between N and other geotechnical parameters that would give an over view of coefficient of correlation R and Root Mean Squared Error (RMSE), in which it was done a general comparative study among ANN and nonlinear regression Analysis by using nine nonlinear models, noting that the best result in each line has been colored in green.

3.3. Comparison of correlation between N and geotechnical parameters:

Overall, it is noted a rise in the proportion of the correlation coefficient R in the ANN method compared to the NRA that is shown from the volatility and a difference in R between the various models exception in rare cases, such as in the sand during the correlation between N and (Yd; e and Cu) where was observed superiority of Fourier model in the first; EXP degree 2 in the second case and Rational term2 in the last, furthermore, there has been observed a relative reduction in root mean square error (RMSE) in the ANN way, compared with the rest of the models with the exception of the examples that have been mentioned before, which confirms the hypothesis that has been put forward that the ANN's way is correlating between different variables without the need to know the nonlinear variable model in addition of its effectiveness to predict various parameters, unlike the NRA mode where it must know the changing model for the best outcomes All these results can be observed through (Fig. 7, Fig. 8, Fig. 9, Fig. 10, Fig. 11, Fig. 12, Fig.13, Fig. 14, Fig. 15, Fig. 16, Fig. 17 and Fig. 18).

Generally with regard to the various correlations between N and other geotechnical parameters, the following results were observed:

1. A strong correlation between N and dry density Yd especially in silty soil using ANN model and sandy soil utilizing Fourier model; with correlation's coefficient respectively (0.91;0.94); In addition to an average correlation in the rest of the soil types with a R Value between (0.57; 0.76) (see Fig. 7).

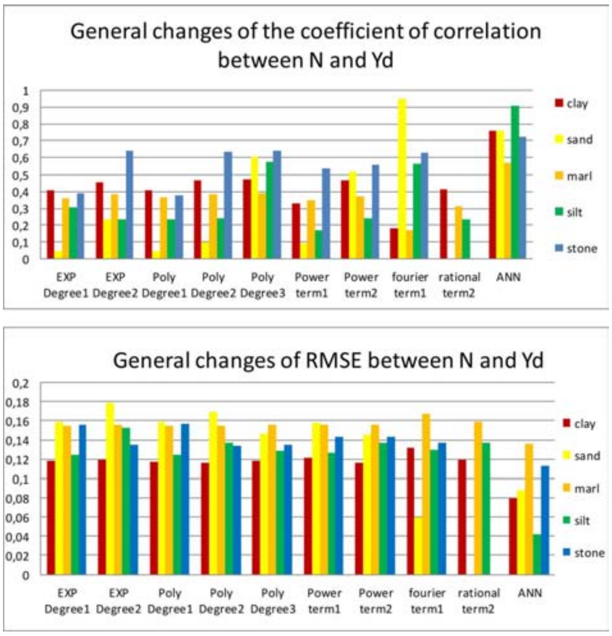


Fig. 7. General change of R and RMSE between Nspt and Yd.

2. A strong correlation between N and wet density Yh especially in the silty soil; with a correlation's coefficient about (0.89); additionally, an average correlation in the rest of the soil types with an R Value between (0.43; 0.62) (see Fig. 8).
3. A strong correlation between N and water content W especially in the silty soil; with a correlation's coefficient about (0.9); furthermore, an average correlation in the rest of the soil types with an R Value between (0.36; 0.58) (see Fig. 9).

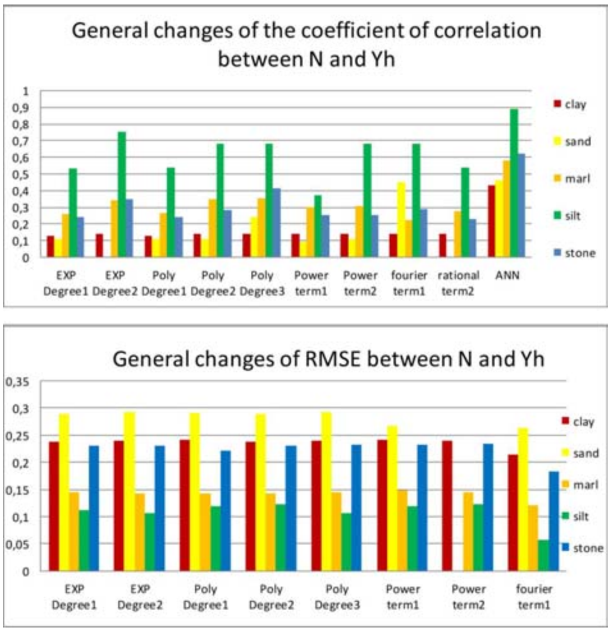


Fig. 8. General change of R and RMSE between Nspt and Yh.

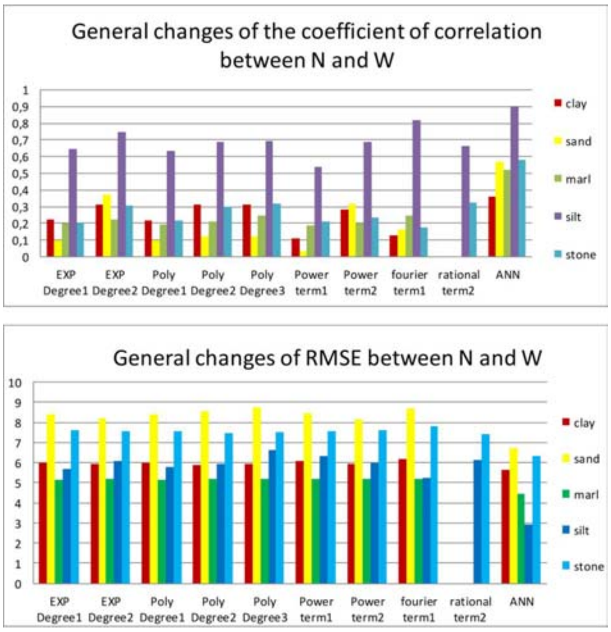


Fig. 9. General change of R and RMSE between Nspt and W.

4. A strong correlation between N and void ratio e especially in the clay and sand; with a correlation's coefficient respectively about (0.83; 0.97); moreover, an average correlation in the rest of the soil types with an R value between (065; 0.7) (see Fig. 10).
5. A strong correlation between N and fine contents FC especially in the silty

soil; with a correlation's coefficient R about (0.82); furthermore, an average correlation in the rest of the soil types with an R value between (0.46-0.48) (see Fig. 11).

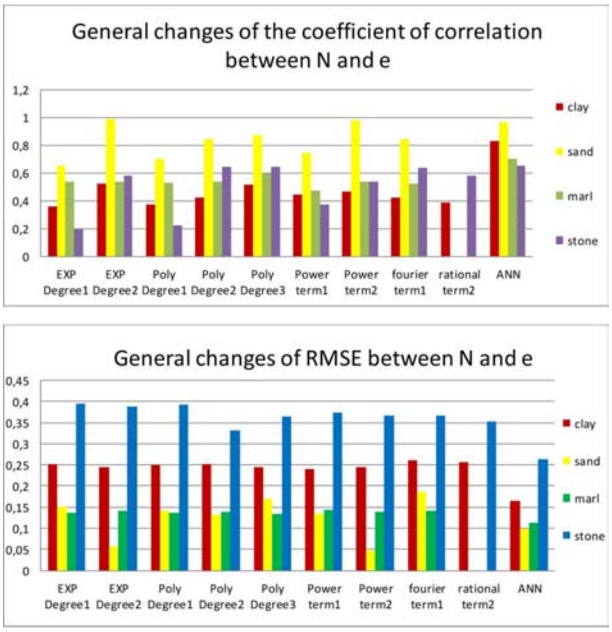


Fig. 10. General change of R and RMSE between Nspt and e.

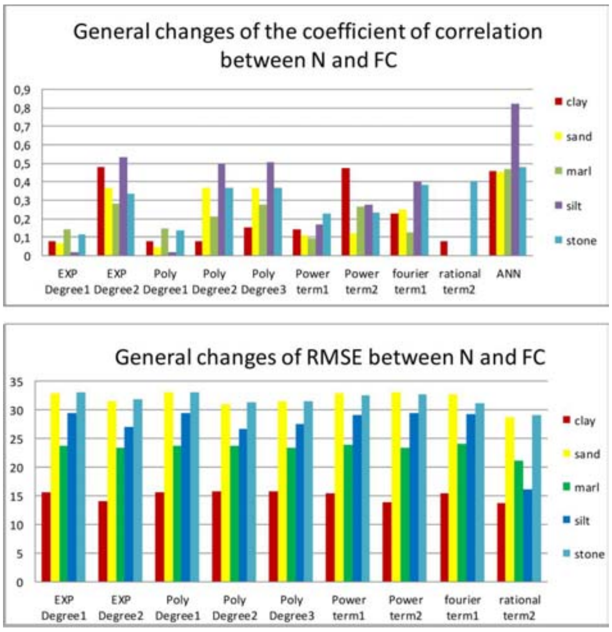


Fig. 11. General change of R and RMSE between Nspt and Fc.

6. A strong correlation between N and median diameter D50 especially in the marl; with a correlation's coefficient R about (0.99); additionally, an average correlation in the rest of the soil types with an R value between (0.6-0.95) (see Fig. 12).

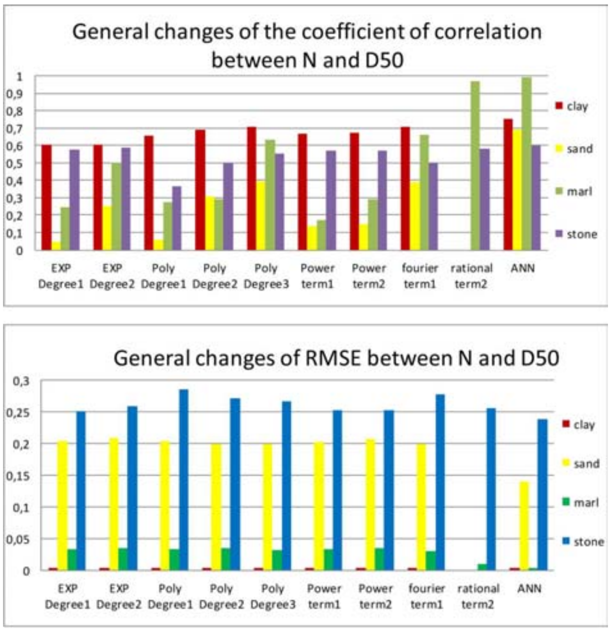


Fig. 12. General change of R and RMSE between Nspt and D50.

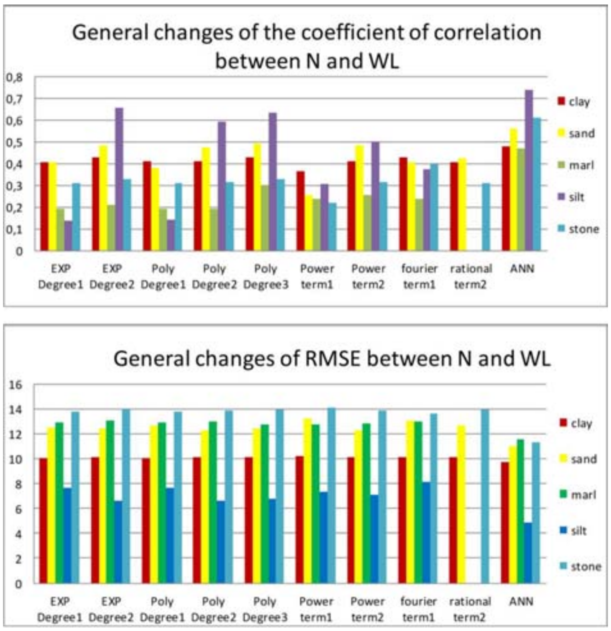


Fig. 13. General change of R and RMSE between Nspt and WL.

7. A medium correlation between N and liquid limit WL with an R value between (0.48-0.74) in all types of soil (see Fig. 13).
8. A strong correlation between N and plastic limit WP especially in the

clayey-sand soil; with a correlation's coefficient R about (0.9); moreover, an average correlation in the rest of the soil types with an R value between (0.5-0.69) (see Fig. 14).

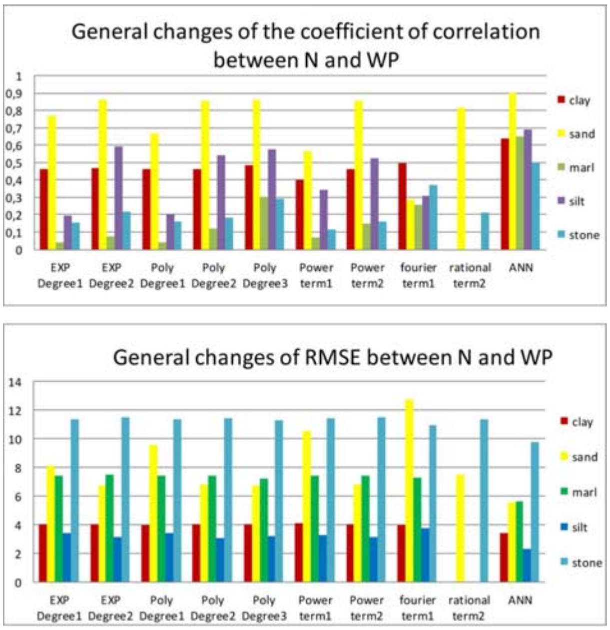


Fig. 14. General change of R and RMSE between Nspt and Wp.

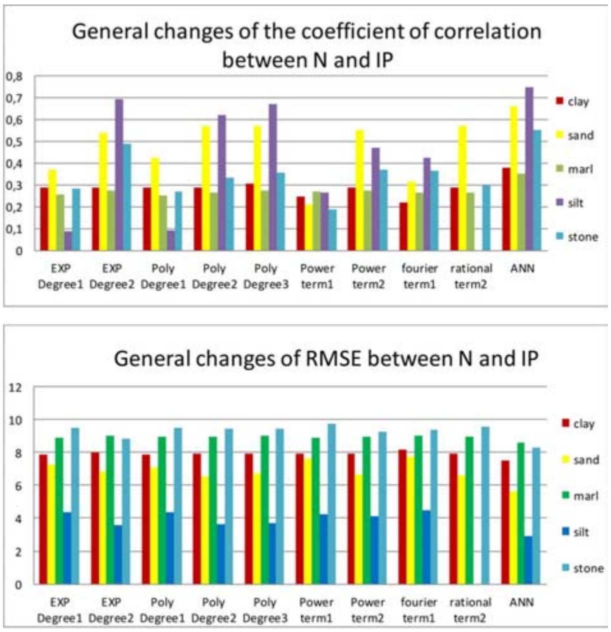


Fig. 15. General change of R and RMSE between Nspt and Ip.

9. A medium correlation between N and plasticity index IP with a R value between (0.35-0.75) in all types of soil (see Fig. 15).

10. A strong correlation between N and consistency index IC especially in the clayey-sand, marl and silt soil; with a correlation's coefficient R respectively about (0.99, 0.88, and 0.84). In addition to an average correlation in the rest of the soil types with an R value between (0.35-0.5) (see Fig. 16).

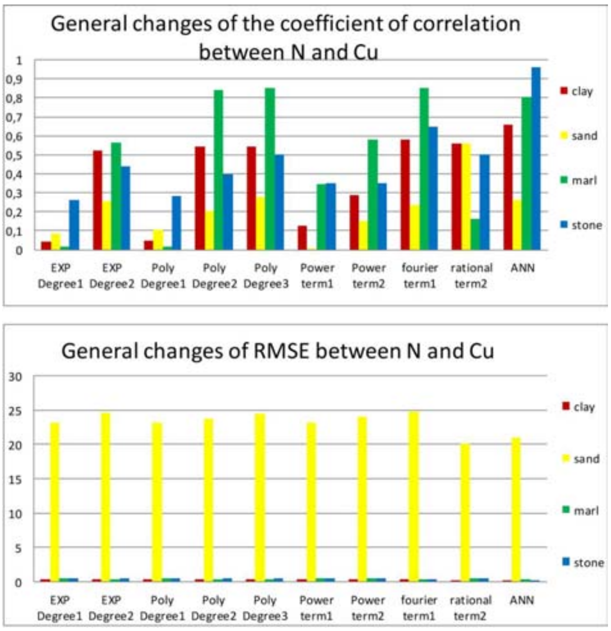


Fig. 16. General change of R and RMSE between Nspt and Ic.

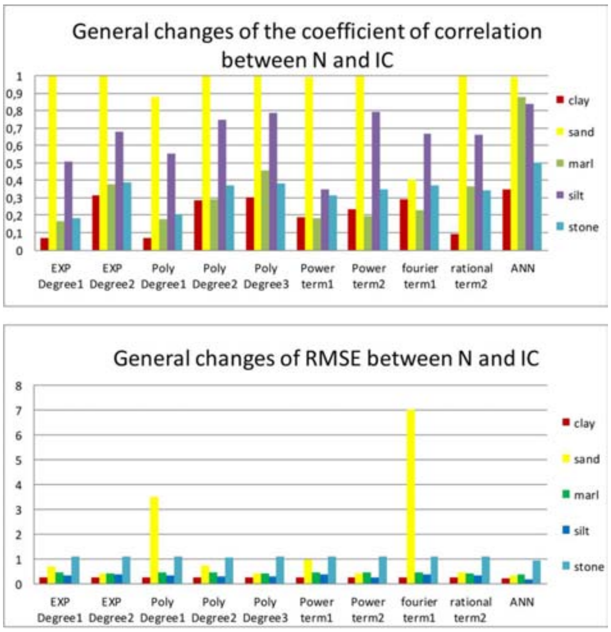
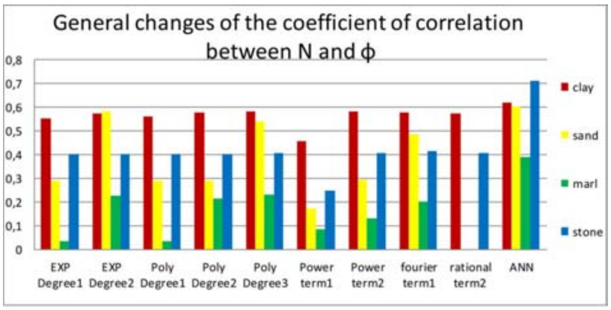


Fig. 17. General change of R and RMSE between Nspt and Cu.

11. A strong correlation between N and cohesion cu especially in the gravel and marl; with a correlation's coefficient R respectively about (0.96, 0.81); on the other side an average correlation in the rest of the soil types with a R value between (0.26-0.62) (see Fig. 17).
12. A medium correlation between N and friction angle with an R value between (0.39-0.71) in all types of soil (see Fig. 18).



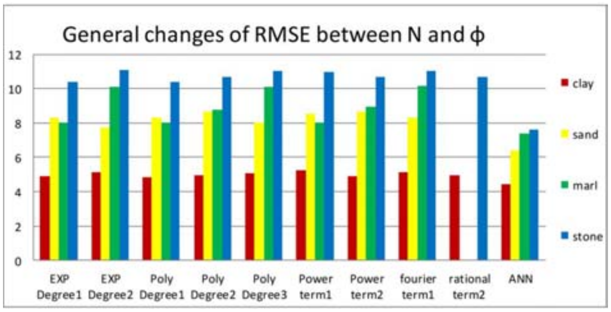


Fig. 18. General change of R and RMSE between Nspt and φ.

4. Conclusions

After treating more than 390 samples in Algiers area, using both methods ANN and NRA in all soil's types, thus trying to correlate standard penetration number (Nspt) to other geotechnical parameters in an effort to predict these parameters from Nspt to shorten the time, effort and money in identifying the various Algerian soil properties, the following results have been drawn:

- Artificial neural networks are a promising tool or methodology to get a fast and reliable estimate of the geotechnical properties, this study has demonstrated their effectiveness to predict various parameters better than nonlinear regression analysis method, which encourages more attention to this aspect in future studies.
- The use of artificial neural networks has proven its effectiveness in predicting the relationship between two variables X and Y whatever the nonlinear degree of complexity between the two variables compared with nonlinear regression analysis where it cannot expect the type of non-linear change between the two variables.
- After using ANN, regarding the Clay, it was observed a high correlation between N and e with a correlation's coefficient (R=0.83), and a moderate correlation between N and other geotechnical parameters with R limited by (0.35-0.76).
- Result of utilizing ANN from sandy soil noting that it exists a strong relationship between N and (e, WP and Ic) with a correlation's coefficient respectively about (0.97; 0.9 and 0.99), in addition to that an average correlation with other geotechnical parameters with R limited by (0.26-0.76).
- The results demonstrate a strong relationship between N and (D50, Ic and Cu) from silty soil with a correlation's coefficient respectively about (0.99; 0.88 and 0.81), and a medium correlation with other geotechnical parameters with R limited by (0.35-0.7).
- Elevated results obtained in the marl soil and expecting it to cause a lack of used samples in the marl soil, causing a extrapolation's weakness in ANN analysis, so a high correlation was noted between N

and (Yd, Yh, W, FC and IC) with a correlation's coefficient respectively about (0.91; 0.89; 0.9, 0.82, 0.84), and a moderate correlation with other geotechnical parameters with R limited by (0.67-0.75).

- Result of gravel proves a strong relationship between N and Cu with a correlation's coefficient R=0.96, and a moderate correlation with other geotechnical parameters with R limited by (048-0.72).

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