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Research Paper

The Neuro-genetic approach for estimating the compression index

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ABSTRACT

In the last decade, a number of empirical correlations have been proposed to connect the compression index to other soil parameters, such as liquid limit, plasticity index and the void index. This paper presents a correlation study between the physical properties and compression index which was conducted on normally consolidated clay by the hybridization of two approaches (artificial neuronal networks and genetic algorithms). A comparison was made between the measured experimentally and predictions compression indexes. The obtained results indicate that the Neuro-genetic model has the ability to accurately predict the compression index thus be used in practice by geotechnicians.

1 Introduction

One of the major problems related to civil engineering structures is that of ground movements with amplitude ranges from a few millimeters to a few meters [1]. This parameter, which has a major influence, is determined experimentally from oedometric tests according to the procedures described in the technical standards (NFP 94-090-1, 1992 or ASTM D4546, 1986), which requires a qualified workforce and a relatively long time. These difficulties have led us to propose a hybrid approach between artificial neural networks and genetic algorithms based on test results simply measured in order to be of considerable interest since it will save time and cost. This article is a continuation of our previous works [2, 3] the preliminary results were obtained with a network driven by an iterative learning mechanism that acts on the gradient descent algorithm. The optimization by this algorithm is not really satisfactory for the identification of weakly influential parameters. Therefore, we proposed to use more advanced methods to analyze geotechnical problems. The final form of the proposed approach (neuro-genetic) composed of artificial neural networks and genetic algorithms, the implantation of the genetic algorithm in

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this study aim to optimize and determine the network's synaptic weights. Our developed model is able to provide accurate parameter prediction (Cc) and to be useful in engineering practice

2 Review of previous work

Since the sixties, many models have been developed by researchers to predict the compression index (Table 1), in order to reduce costs and save time. A simple regression analysis aims to verify the validity of available correlations between the Compression index (Cc) and other soil properties [4]. Singh and Noor proposed a correlation between Compression Index (Cc), Liquidity Limit and Plasticity Index. The model based on the multiple regression analysis gave a minimal error (RME = 0,035) compared to those of Skempton (RME = 0.131); Terzaghi and Peck (RME = 0,211) [5]. Yoon et al. proposed empirical equations using natural water content, initial void index, liquidity limit, and plasticity index for clay soils in the coastal zone of Korea, for well correlated parameters, the linear regression model produced relatively satisfactory results [6]

Table 1: The empirical equations for estimating the compression index.

Inputs	Equations	Authors
LL, G_s	$Cc = 0.2343 \times LL \times G_s$	Nagaraj et Murthy [18]
	$Cc = 0.2926 \times LL \times G_s$	Park et Lee [19]
w_n, LL	$Cc = 0.009 \times w_n + 0.005 \times LL$	Koppula[20]
	$Cc = 0.009 \times w_n + 0.002 \times LL - 0.1$	Azzouz et al [17]
e_0, w_n	$Cc = 0.4 \times (e_0 + 0.001 \times w_n - 0.25)$	Azzouz et al [17]
e_0, LL	$Cc = -0.156 + 0.411 \times e_0 + 0.00058 \times LL$	KhafajiandAndersland[21]
	$Cc = -0.023 + 0.271 \times e_0 + 0.001 \times LL$	Ahadian et al [22]
e_0, w_n, LL	$Cc = 0.37 \times (e_0 + 0.003 \times LL + 0.0004 \times w_n - 0.33)$	Azzouz et al [17]
	$Cc = -0.404 + 0.341 \times e_0 + 0.004 \times LL + 0.006 \times wn)$	Yoon and Kim [6]
LL	$Cc = 0.009 \times (LL - 10)$	Terzaghi and Peck [23]
	$Cc = 0.007 \times (LL - 7)$	Skempton[24]
	$Cc = 0.009 \times (LL - 2)$	Phi Hong Thinh et al [25]
	$Cc = 0.0045 \times LL - 0.01246$	Hamza Güllü et al [26]
w_n	$Cc = 0.00553 \times w_n + 0.05321$	Hamza Güllü et al [26]
e_0	$Cc = 0.08358 \times e_0 + 0.12739$	Hamza Güllü et al [26]
	$Cc = 0.156 \times e_0 + 0.0107$	Onyejekwe et al (2014) [27]
e_0, LL	$Cc = 0.004483 \times LL + 0.028871 \times e_0 - 0.03029)$	Hamza Güllü et al [26]
	$Cc = 0.173 \times (1 + e_0) \times (Ln(LL) - 3.01)$	Mccabe et al [28]
G_s, e_0	$Cc = 0.141 \times {G_s}^{1.2} \left[\frac{(1 + e_0)}{G_s}\right]^{2.38}$	Herrero [29]

Abbasi et al. suggested a correlation model between the physical properties and the compression index (Cc) by statistical data analysis software (SPSS). The choice of independent variables was guided by the principle of parsimony [7]. Kalantary and Kordnaei also used the same database to predict a new correlation by artificial neural networks. The advantage of this method is that it aims at mitigating the disadvantages of significant multicollinearity, which manifests itself in many multiple regression problems [8]. Shahin et al. showed that despite soil variability and its complex behavior, artificial neural networks can be used to predict with a good approximation geotechnical and geological soil model [9], Tang et al. found that when the number of input variables increases the predictive capacity of the neural network improves [10]. Tang et al. also suggested that even with little data, the neural network can perform reasonably well if the input parameters are significant [10]. Despite the effectiveness of neural networks, which have proven to be powerful prediction tools thanks to their ability to learn, generalize and classify, there are still problems related to their learning styles: the learning time is slow, initial parameters can have considerable effects on the concepts learned, there are no methodologies for choosing a network topology appropriate to the given problem and their inability to explain the results they provide. These limitations have led to the proposal of hybridizations with other techniques such as genetic algorithms to overcome the drawbacks and limitations of this paradigm, while improving the prediction rate. The interaction between the processes of learning and evolution is much studied. She has shown her interest in the field of optimization in the form of so-called "hybrid" algorithms combining a genetic algorithm and a neural network. A number of studies have investigated the dynamics of this interaction. The first combination of genetic algorithms and neural networks was applied in the late 1980s by Miller et al. [11], followed by intense research in the 1990s by Kinato and Schiffmann et al.[12, 13].Abbas and Musbah [14] have developed a hybrid neuro-genetic model for pattern recognition. This model consists of two steps, a first where a genetic algorithm is used to find an initial weight configuration for the second phase. For the latter, the best initial weight vector will be considered for the learning of the neural network by the algorithm of the back-propagation of the gradient. The results are satisfactory because they ensure the possibility to accelerate the speed of convergence and reduce the number of epochs to less than 50%. In a previous paper Bourouis et al. we tested the efficiency of neuro-genetic to predict the California bearing ratio after immersion (CBRimm) [2]. The aim of using genetic algorithms is to ensure rapid convergence of the error function. We have shown that a neuro genetic approach was able to predict the CBRimm index accurately. Smith cited that if $| R | > 0.8$ implies the existence of a strong correlation, if $0.2 <| R | <0.8$, this means the appearance of a correlation and if $| R | <0.2$, a weak correlation existing[15]. Willmott and Matsuura examined the relative squared error (RMSE) and average absolute error (MAE) capabilities to describe the average error in model performance[16].The results indicate that MAE is a measure of the actual average error trend (unlike RMSE).

3 Methodology

The analysis tools used in this study include two approaches: artificial neuronal network (RNA) and neuro-genetic (NG).In a first time we were interested in the contribution of different learning algorithms and in a second time the effect of number of neurons in each layer was tested, in order to minimize the cost function. The second approach is to solve the learning problem using a local search method. Starting from an initial weight configuration, the method will look for the best solution in the vicinity of this configuration.

3.1 The database

In this paper we used a database created by Kalantary and Kordnaei [8] which is composed of a large set of (391 measures). The input variables used are: e_0, w_n, G_s, LL and PL. Table 2 summarizes the ranges of variation and the average values of the parameters.

Table 2: Variation and mean values of the properties of the material used[8].

Parameters	LL (%)	PL (%)	w_n (%)	e_0	G_s	C_c
Interval of values	[24.0-81.0]	[3.0-50.0]	[10.2-70.0]	[0.36-1.88]	[2.43-2.80]	[0.05-0.63]
Averages	39.84	18.69	28.67	0.77	2.64	0.2

The database was divided into three parts: Learning (330), Testing (10) and validation (51). The set of learning data was used to train the ANN model, the set of validation data was used to stop the learning process and the set of test data was used to assess the model performance.

3.2 The matrix of Pearson correlations

This step aims to detect the presence or absence of a linear relationship between two continuous quantitative characteristics and reduce the risk that the neural networks are only within the local minimum values. This coefficient varies between -1 and +1. The interpretation is given in Figure 1.

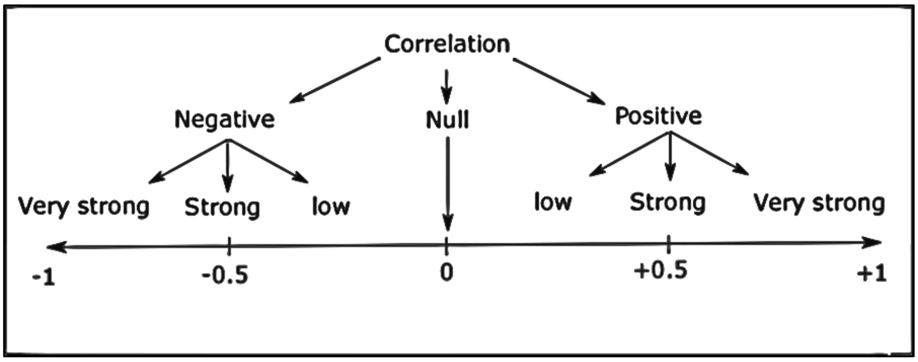


Figure 1: The Pearson coefficient interval

The test results shown in Table 3 indicate that e_0 and w_n have a better correlation with the compression index Cc than other parameters such as LL, PL and G_s.

Table 3: Pearson correlation matrix

	LL	PL	w_n	e_0	G_s	Cc
LL	1					
PL	0.97	1				
w_n	0.33	0.29	1			
e_0	0.31	0.27	0.90	1		
Gs	-0.25	-0.24	-0.005	0.11	1	
Cc	0.40	0.37	0.74	0.81	-0.16	1

3.3 Artificial neural networks

Our choice is then made on multi-layer perceptron (MLP), which is generally driven by the back-propagation algorithm. These networks have been successfully applied to a multitude of classification issues. The MLPs are the most widely employed and have demonstrated their skills, particularly for complex problems. The studied network is a feed-forward multilayer perceptron type with a learning algorithm resilient Retro-propagation. This algorithm is simple with fast convergence and learning requires a minimum storage. Logistic sigmoid transfer function is used for the two hidden layers, the output is activated by the linear function to get desired results. Learning rate of 0,005 is found to be suitable for good performance. To determine the best network architecture (the optimal number of neurons) we have fixed all parameters as (number of hidden layers, the type of activation function, learning algorithm) and varied the number of neurons in the hidden layers and then takes the test with the minimum mean absolute error (MAE).

3.3.1 Experimental validation of the RNA model

Five models have been developed (RNA1, RNA2, RNA3, RNA4 and RNA5) to estimate the compression index (Cc), Table 4 below, shows the different parameters selected after optimization.

Table 4: The average absolute errors of the test for each model

Output	Algorithm	Model	Input	Network Architecture	MAE Test
Cc	trainrp	RNA1	LL, PL	2-25-30-1	0,089
		RNA2	e_0, w_n	2-19-16-1	0,032
		RNA3	e_0, w_n, PL	3-38-06-1	0,038
		RNA4	e_0, w_n,PL,LL	4-21-48-1	0,024
		RNA5	LL, PL, w_n, e_0, G_s	5-31-37-1	0,027

The use of the parameters that influence the RNA2 model provides a reliability prediction over RNA1 model. The average absolute error of the model test is 0,032. The addition of other input variables of the network RNA4 has improved the performance models with mean absolute errors of test 0,024 (Table 4). Similar studies have shown that more the number of input is bigger more the model gives better performances Tang et al. [10]. The histogram of the differences between the measured values and those calculated was drawn to find the best of these four networks (Figure 2).This histogram confirmed that the network with four variable input (e_0, w_n, PL, LL) gives the better result

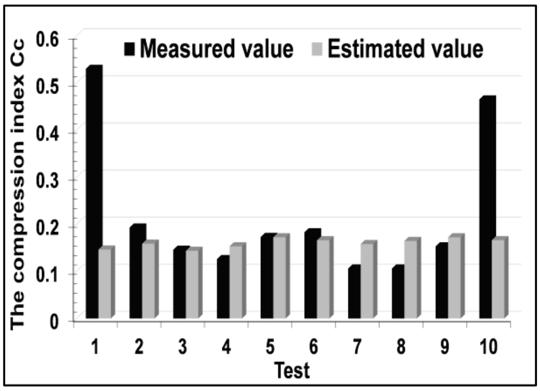
3.4 Neuro-genetics

Neural networks and genetic algorithms have their own specific characteristics, offer advantages and suffer from several limitations at the same time. To overcome these limitations, current artificial intelligence (AI) work has shifted to hybrid systems. In this paper, the genetic approach is used to determine the synaptic weights of neural networks. The input and output data were normalized by the logarithmic function to obtain good network behavior.

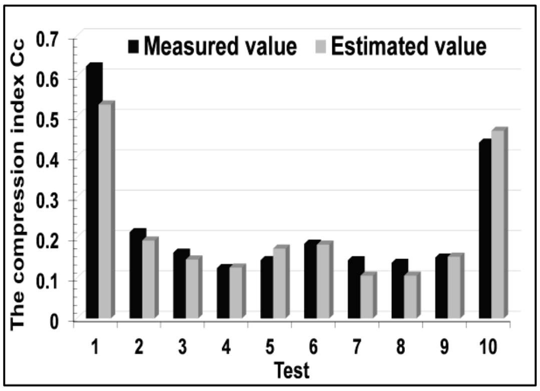
Table 5: The average absolute errors of the test for each model

Output	Algorithm	Model	Input	Network Architecture	MAE Test
Cc	GA	NG1	LL, PL	2-25-30-1	0,0889
		NG2	e_0, w_n	2-19-16-1	0,0293
		NG3	e_0, w_n, PL	3-38-06-1	0,0228
		NG4	e_0, w_n, PL, LL	4-21-48-1	0,0219
		NG5	LL, PL, w_n, e_0, G_s	5-31-37-1	0,0175

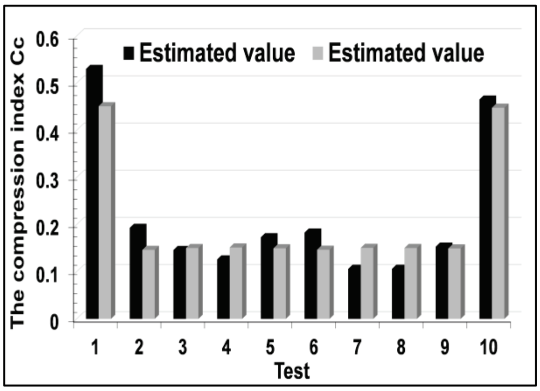
The set of data used to develop the model is divided into two parts: one for learning and the other for testing. The training set is used to determine the values of significant network weights. The work is started by creating a random generation. 100 were chosen as the size of the initial population. To generate an initial population and minimize the number of errors we must limit the search space. The wheel roulette method has been used for the operator of selection, for the crossover and mutation; applied probabilities are 0.9 and 0.01 respectively. The evolutionary process was repeated until the error becomes minimal. The ability of each network is determined by calculating the mean square error (MAE) at the neural network.



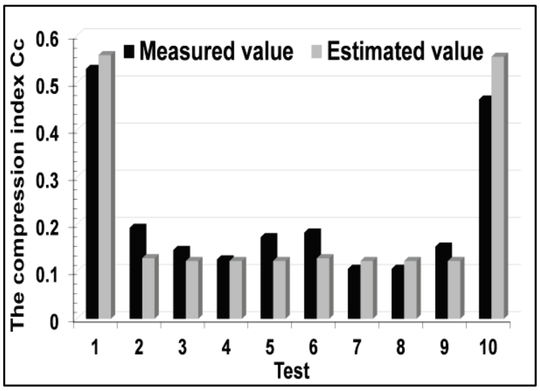
(a) : The difference between predicted and measured values calculated by the model RNA1



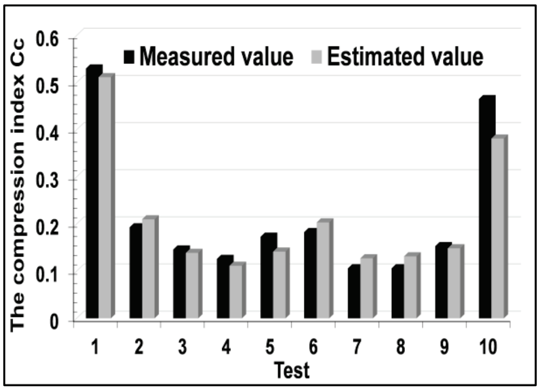
(b) : The difference between predicted and measured values calculated by the model RNA2



(c) : The difference between predicted and measured values calculated by the model RNA3



(d) : The difference between predicted and measured values calculated by the model RNA4



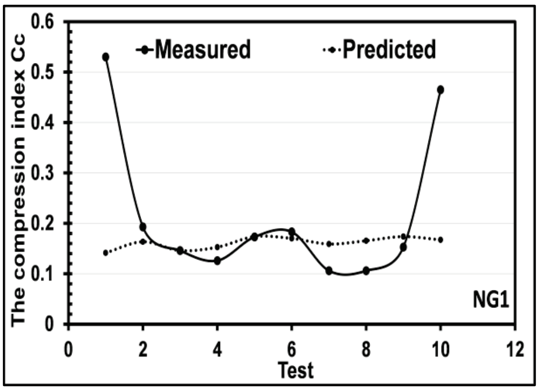
(e) : The difference between predicted and measured values calculated by the model RNA5

Figure 2: The difference between predicted and measured values calculated by RNA model

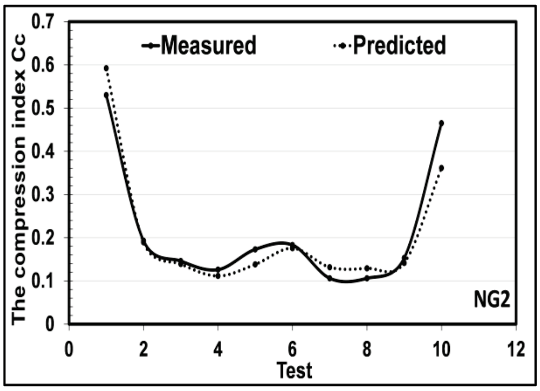
3.4.1 Experimental Validation of NG model

To choose the most efficient network we proposed five predictive models (NG1, NG2, NG3, NG4, and NG5). The approach used is to combine the GA and ANN, for the benefits of each of these two methods. The results obtained are shown in Table 5.

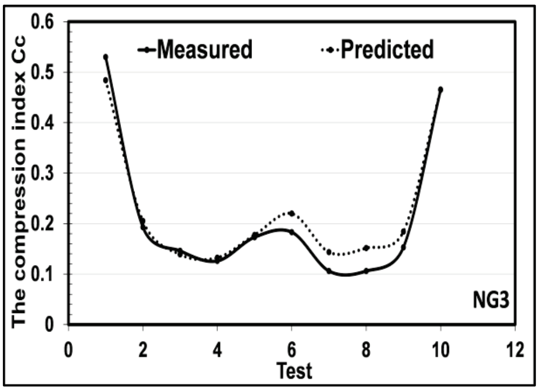
The fifth model (NG5) gives very good results with an average absolute error not exceeding 0,018 (Figure 3-e). Nevertheless we note in passing the cons-performance obtained by the NG1 model (Figure 3-a) with an average absolute error neighbors of 0,089 due to the reducing of the number of input variables, NG5 the model seems to be representative because the values are quite close to those measured directly. It can therefore be used to obtain approximate values of the compression index.



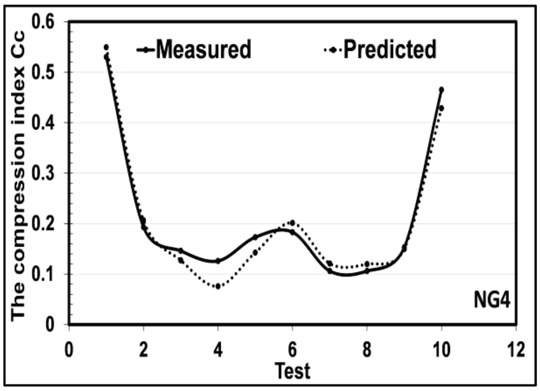
(a) : Comparison between predicted and measured values (NG1)



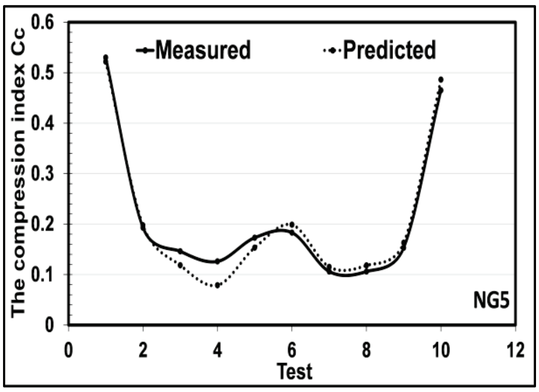
(b) : Comparison between predicted and measured values (NG2)



(c) : Comparison between predicted and measured values (NG3)



(d) : Comparison between predicted and measured values (NG4)



(e) : Comparison between predicted and measured values (NG5)

Figure 3: Comparison between predicted and measured values by NG

4 Comparison between RNA, NG and empirical models

Several authors have proposed empirical relationships based on the correlation between the physical properties and compression index, the NG models and RNA were tested with no learned examples and results were compared with the empirical models. Three other statistical indicators have been brought in this part to compare the fits obtained by using different methods; (MSE) which represents Mean Square Error, (RMSE) the square root of MSE and (MAPE) the Mean absolute percentage error. The following table (Table 6) shows the results of the empirical models of the previous work as well as those obtained by the proposed method in decreasing order of the value of MAE in order to highlight the power and the performance of the models studied here.

Table 6: The performance of empirical and developed models

Authors	Inputs	MAE	MSE	RMSE	MAPE	R
Khafaji and Andersland (1992) [21]	LL, e_0	0.2804	0.0798	0.2825	170.23	0,97
Koppula (1981) [20]	LL, w_n	0.2405	0.0637	0.2524	147.97	0,88
Phi Hong Thinh et al. (2017) [25]	LL	0.1485	0.0313	0.1770	99.95	0.40
Park and Lee (2011) [19]	LL, G_s	0.1273	0.0226	0.1504	81.82	0,42
Skempton (1944) [24]	LL	0.1045	0.0183	0.1354	51.88	0.40
Terzaghi and Peck (1967) [23]	LL	0.1043	0.021	0.1450	63.62	0.40
Hamza Güllü et al. (2016) [26]	LL	0.1038	0.0205	0.1432	42.87	0.40
Nagaraj and Murthy (1985) [18]	LL, G_s	0.0982	0.0172	0.1310	53.56	0,42
Hamza Güllü et al. (2016) [26]	LL, e_0	0.0975	0.0180	0.1340	40.37	0.53
RNA1	LL, PL	0.0893	0.0245	0.1565	30.39	0,20
NG1	LL, PL	0.0889	0.0248	0.1575	30.10	0,31
Onyejekwe et al. (2015) [27]	e_0	0.0858	0.0155	0.1244	31.78	0.98
Mccabe et al. (2014) [28]	LL, e_0	0.0840	0.0134	0.1158	42.99	0.66
Yoon and Kim (2006) [6]	LL, e_0, w_n	0.0826	0.0119	0.1091	42.57	0,94
Hamza Güllü et al (2016) [26]	e_0	0.0744	0.0138	0.1173	30.43	0.98
Hamza Güllü et al (2016) [26]	w_n	0.0550	0.0053	0.0725	26.94	0.96
Azzouz et al (1976) [17]	LL, w_n	0.0472	0.0032	0.0569	26.38	0,94
Ahadian et al (2008) [22]	LL, e_0	0.0427	0.0027	0.0524	23.34	0,97
RNA3	e_0, w_n, PL	0.0379	0.0021	0.0456	18.71	0,98
Rendon-Herrero (1983) [29]	G_s, e_0	0.0355	0.0030	0.0549	14.67	0,97
RNA2	e_0, w_n	0.0325	0.0015	0.039	18.54	0,97
NG2	e_0, w_n	0.0293	0.0017	0.0418	12.98	0,96
Azzouz et al (1976) [17]	e_0, w_n, LL	0.0289	0.0011	0.0330	14.71	0,98
Azzouz et al(1976) [17]	e_0, w_n, LL	0.0274	0.0013	0.0358	12.80	0,97
RNA5	e_0, w_n, PL, LL, G_S	0.0266	0.0014	0.0371	13.25	0,97
RNA4	e_0, w_n, PL, LL	0.0244	0.0010	0.0323	12.31	0,98
NG3	e_0, w_n, PL	0.0228	0.0008	0.0286	14.63	0,99
NG4	e_0, w_n, PL, LL	0.0219	0.0006	0.0254	12.80	0,99
NG5	e_0, w_n, PL, LL, G_S	0.0175	0.0004	0.0212	11.13	0,99

To evaluate the performance of NG and RNA models simultaneously, the MAE parameter and the correlation coefficient will be examined. The performances of the two models used for prediction of compression index Cc are given in Table 6.The model NG5 provides significant results with an average absolute error less than 0,018 and a correlation coefficient equal to 0,99. The study shows that the use of a sufficient number of inputs in the NG models ensures properties prediction reliability of the ground (Figure 4), RNA performance will definitely be improved with a wider and more representative database with a sufficient number of inputs.

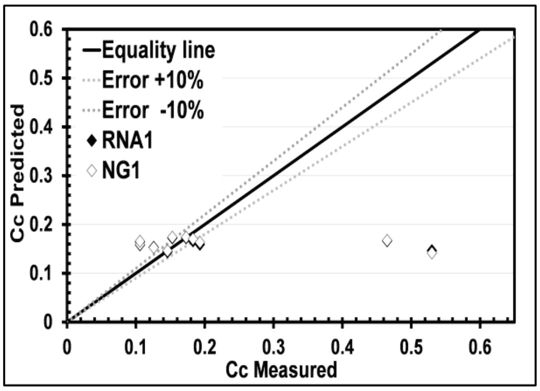


Figure 4-a: Comparison between the RNA1 and NG1 models

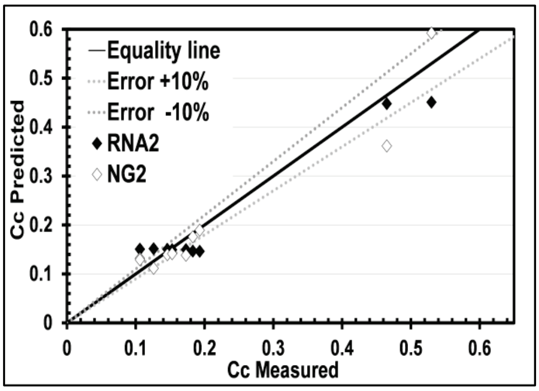


Figure 4-b: Comparison between the RNA2 and NG2 models

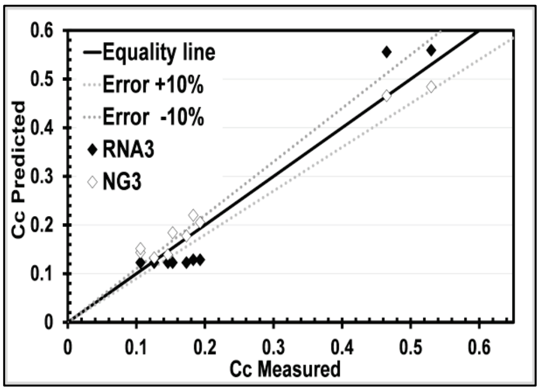


Figure 4-c: Comparison between the RNA3 and NG3 models

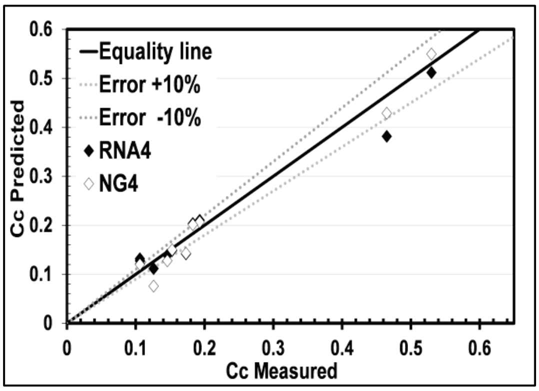


Figure 4-d: Comparison between the RNA4 and NG4 models

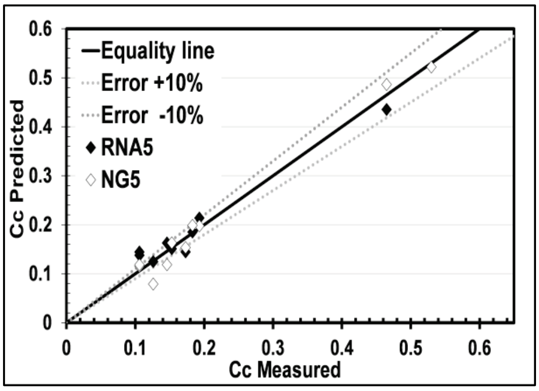


Figure 4-e: Comparison between the RNA5 and NG5 models

Figure 4: Comparison between RNA and NG approach in an interval error of -10% and +10%

5 Conclusion

In this paper, the application of several intelligent models was investigated to find the most powerful model for prediction of the compression index. The applied intelligent approaches were RNA and NG model. The aim to use the genetic algorithm in the neuro genetic model is to optimize and determine the network's synaptic weights. Several statistical errors were calculated to determine the accuracy of each one. The developed intelligent models show high accuracy over empirical correlations. In addition, NG5 model showed the most accurate prediction in comparison with other models for all data. The results shows that the predicted compression index values using proposed NG model are compatible with those measured.

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