Design of neural networks by using genetic algorithm for the prediction of immersed CBR index

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Abstract

The most important parameter of soil for the conception of flexible pavements is the California Bearing Ratio after immersion (CBR_{imm}). This parameter is determined from laboratory testing, which requires skilled workforce and time. Based on parameters simply measured like Maximum Dry Density (MDD), Optimum Moisture Content (OMC), Liquid Limit (LL), Plastic Limit (PL) and the fine fraction passing at 0.08 mm and 2 mm ($F_{0.08\ mm}$, F_{2mm}) we proposed a neuro-genetic model to predict the index CBR_{imm} The aim to use the genetic algorithm is to evolve at the same time: The determination of the artificial neural network architecture, transfer function and the optimization of synaptic weights. Using a neuro-genetic approach helps to increase neural network performance and it gave us a minimal average absolute error.

Keywords: CBR_{imm}, Compacting, Prediction, Artificial neural network, Genetic algorithm.

1. INTRODUCTION

During the work of excavation of earth dams, road embankments and slopes of the airport it is necessary to compact mechanically the material to increase its shear strength and reduce its permeability. To simulate the compacting procedure to be adopted which ensures a certain level of compactness on site, laboratory tests have been developed for many years; they differ only in the level of energy applied to the soil sample. The CBR California Bearing Ratio test takes a lot of time and requires skilled labor. For this reason, several correlations by various researchers have been developed to estimate this fundamental parameter. In this study we proposed a hybrid model between the artificial neural network and the genetic algorithms in order to predict this index accurately. The role of the genetic algorithm in this work is to optimize the structure of the network and to determine its synaptic weights. The input variables of our model are simply measured parameters such that Optimum moisture content (OMC), maximum dry density (MDD), liquid limit (LL), The fine fraction passing at 0.08 mm ($F_{0.08\ mm}$), and the fraction passing at 2 mm ($F_{2\ mm}$).

2. LITERATURE REVIEW

Geotechnical properties of soils are controlled by factors such as mineralogy, fabric, and pore water, and the interactions of these factors are difficult to establish solely by traditional statistical methods due to their interdependence. Shahin et al (2008) showed that despite soil variability and complex behavior, artificial neural networks (ANN) can be used to predict the geotechnical and geological model of soils with a good approximation [1]. Ripley (1996) indicate that the use of more than one layer hidden in ANN methodology provides the flexibility needed to model complex phenomena [2]. Patel and Desai (2010) proposed a correlation between the plasticity index, the optimum dry density, the optimum Proctor water content and the CBR_{imm} of the alluvial soils [3]. Roy et al. (2007) has developed a multiple regression model. He chose MDD and OMC as input parameters because they have a strong correlation with CBR_{imm}. The model gave satisfactory results with a coefficient of determination equal to 0.982 [4]. Rakaraddi and Gomarsi (2015) proposed a multiple linear regression model to predict the CBR from the liquid limit, plastic limit, percentage of fines and soil density. Bad result for a coarse soil because of the ignorance of the percentage of sand and gravel in the model [5]. Tang et al. (1991) found that when the number of input variables increases the predictive capacity of the neural network improves [6]. The same authors also suggested that even with little data, the neural network can perform reasonably if the input parameters are significant [6]. Pradeep Kumar and Harish Patel (2016) proposed models based on the neural and statistical approach, the neural network model with five input parameters; MDD, OMC, LL, PL and PI gave the best result with an average square error equal to 0.13 [7]. The modeling power of the artificial neural network relies on the transfer functions used. Several works have studied the effects of transfer functions on the performance of neural models, such as Falode and Udombosoont (2016) which used the symmetric saturated linear function; this saturation effect will severely limit the possibility of the network to capture The Input-Output relationship when the problem is complex [8]. The derivation and the simplicity of the sigmoid function calculation logically led Philip et al. (2011) And Bourouis et al. (2015) to use [9-10]. Smith (1986) stated that if $|R| > 0.8$ implies the existence of a strong correlation, if $0.2 < |R| < 0.8$, this means the occurrence of a correlation and if $|R| < 0.2$, a weak existing correlation [11]. Willmott and Matsuura examined relative RMSE and Mean Absolute Error (MAE) to describe the average error in model performance. The results indicate that MAE is a measure of the actual average error trend (unlike RMSE). Our contribution is intended in this sense and exploits the works cited above [12].

3. DESCRIPTION OF THE APPROACHES USED

3.1. GENETIC ALGORITHM (GA)

Genetic algorithms are a family of heuristic algorithms for finding the optimum or near-optimum of any functions, called objective basis on which it is necessary to make any particular hypothesis as decent gradient algorithms regarding their derivability. Genetic algorithms manipulate a population of individuals of constant size, this population of constant size is subject to competition between individuals. Each individual is given as a single string of characters called a chromosome and represents a point in the search space [13]. Using selection, crossing and mutation operators based on natural phenomena, the genetic algorithm evolves this population of individuals over generations (Figure 1).

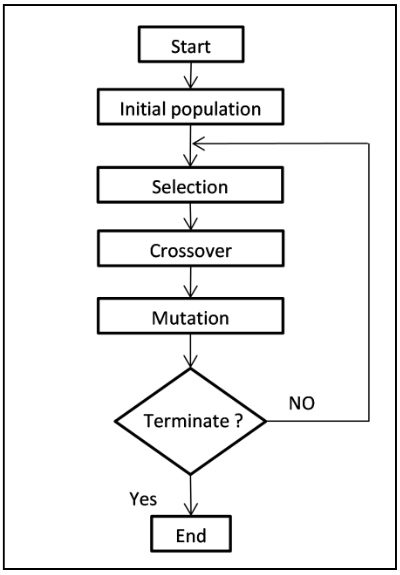


Figure 1: Flow Chart of the genetic algorithm

Crossing and mutation are responsible for exploring the research space by building new individuals from the previous generation, while selection favors individuals who have a high adaptation. Genetic algorithms offer the possibility of finding solutions to very varied problems when it is possible to express these problems in terms of objective function optimization.

3.2. ARTIFICIAL NEURAL NETWOR

Neural networks are a real way to solve several problems where classical methods have shown their limitations. Neural networks, with their classification, memory, filtering and approximation skills, have become a very effective way. The gradient propagation (BP) is a learning algorithm, the problem of this algorithm that it converges very difficult in the case of complex neural networks and the error function is minimized with several local optima because the error surface of a complex network includes many maxima and minima (Figure 2). This means that the gradient algorithm can converge to a minimum which is not the global optimum. The researchers know well that the choice of network architecture can lead to the success or failure of an application, in order to ensure a good performance. We used intelligent search methods namely genetic algorithms where optimization of these parameters is done in an automatic way. The application of genetic algorithms to determine an optimal network structure will be the subject of our study.

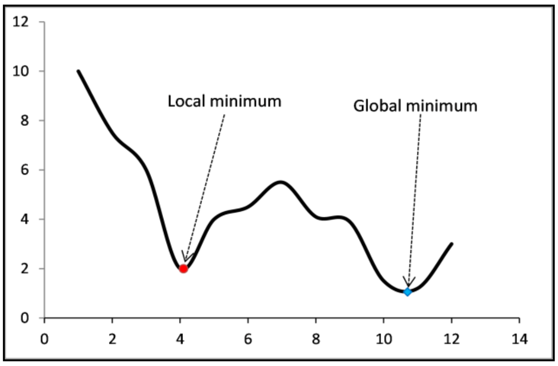


Figure 2: Minimum local and total of the solution

4. PREDICTION OF CBR_{IMM} OF SOILS USING NEURO GENETIC (NG)

In this work we used a database of 220 measurements collected from the laboratory of public works of the west (LTPO - Unit of Tlemcen). Content of optimal Proctor (OMC), dry density (MDD), liquidity limit (LL), the fine fraction passing at 0.08 mm ($F_{0.08\ mm}$) and the fraction passing at 2 mm ($F_{2\ mm}$) are used as input variables in the model developed for the CBR_{imm} index. The characteristics of the samples used in this study are defined in the Table 1.

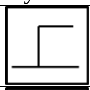
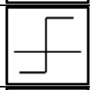
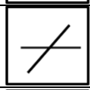
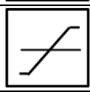
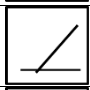
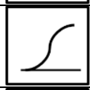
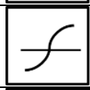
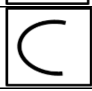
Table 1: The characteristics of the samples used

Type of data	Symbol	Range
Input	$F_{0.08\ mm}$	5.0-79
	$F_{2\ mm}$	12.0-99
	LL	13-65
	OMC	3.0-18
	MDD	1.65-2.35
Output	CBR_{imm}	1.9-100

4.1. METHODOLOGY

The strategy for obtaining RNA optimized by genetic algorithms is based on the development of a program on Matlab, comprising two parts; in a first step, we start by choosing the transfer functions summarized in the Table 2 and find the number of neurons in each hidden layer. In a second time we fix the network parameters (number hidden layers, the number of neurons in each layer, type of the neuron activation function) and optimize the synaptic weights to minimize the error function.

Table 2: The functions of transfer

Name of the function	Relation Input /Output	Symbol
Threshold	$a = 0 \;\; si \;\; n < 0$ $a = 1 \;\; si \;\; n \geq 0$	
Symmetric threshold	$a = -1 \;\; si \;\; n < 0$ $a = 1 \;\; si \;\; n \geq 0$	
Linear	$a = n$	
Linear saturated	$a = 0 \;\; si \;\; n < 0$ $a = n \;\; si \;\; 0 \leq n \leq 1$ $a = 1 \;\; si \;\; n > 1$	
Symmetric saturated linear	$a = -1 \;\; si \;\; n < -1$ $a = n \;\; si \;\; -1 \leq n \leq 1$ $a = 1 \;\; si \;\; n > 1$	
Positive Linear	$a = 0 \;\; si \;\; n < 0$ $a = n \;\; si \;\; n \geq 0$	
Sigmoid	$a = \frac{1}{1 + e^{-n}}$	
Hyperbolic tangent	$a = \frac{e^{n} - e^{-n}}{e^{n} + e^{-n}}$	
Competitive	$a = 1 \;\; if \; n \; maximum$ $a = 0 \;\; if \; other$	

We adopted two layers hidden because it is considered suitable and adequate for good performance [2]. Performances were evaluated using the mean absolute error (MAE) and the correlation coefficient (R)

4.2. ANALYSIS BY THE SIMPLE REGRESSION

A simple regression analysis was performed to identify useful input parameters that they have a good correlation with the CBR_{imm} index. The aim of this step is to reduce the risk that neural networks will remain in local minima. The results of this analysis are presented in Figure 3 for the five parameters $F_{0.08\ mm}$ (Figure 3.a), F_{2mm} (Figure 3.b), LL (Figure 3.c), OMC (Figure 3.d) and MDD (Figure 3.e).

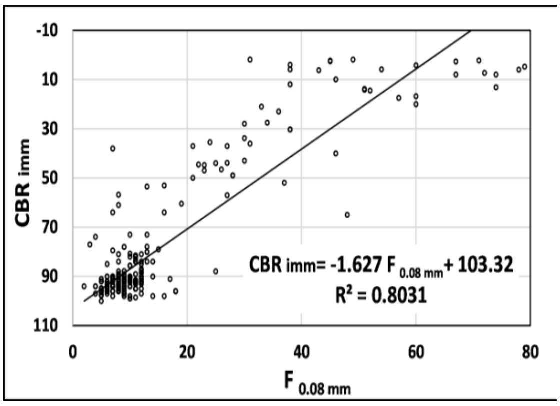


Figure 3.a: Simple regression for the parameter $F_{0.08\ mm}$

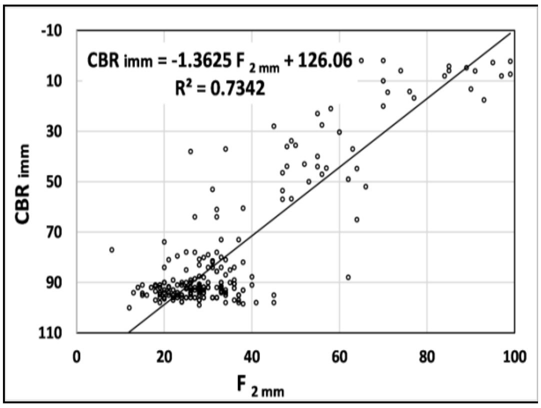


Figure 3.b: Simple regression for the parameter $F_{2\ mm}$

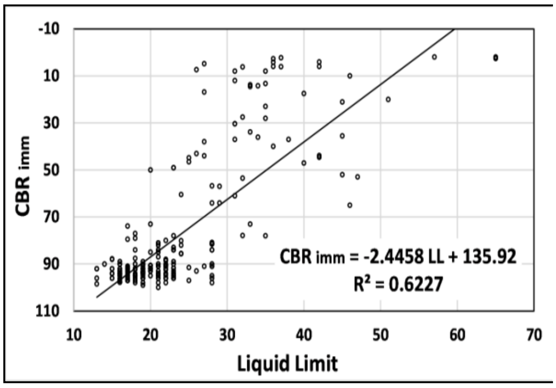


Figure 3.c: Simple regression for the parameter LL

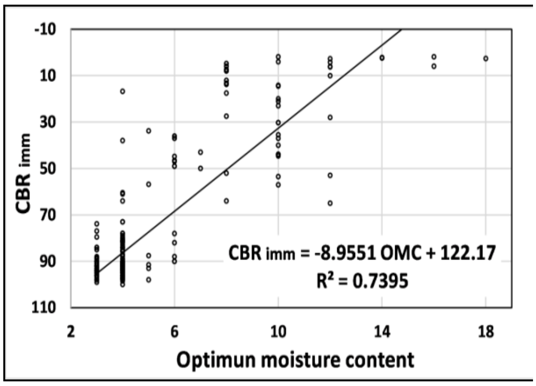


Figure 3.d: Simple regression for the parameter OMC

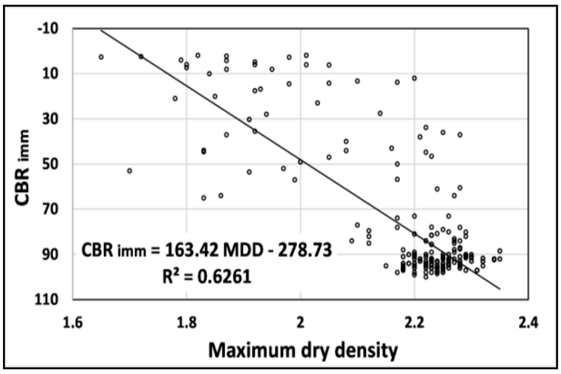


Figure 3.e: Simple regression for the parameter MDD

As shown: The input parameters have a linear relationship with the CBR_{imm} index and they bear a better correlation with the output with a coefficient of determination between 0.62 and 0.81.

4.3. ANALYSIS BY PROPOSED MODEL

For the prediction of the CBR_{imm} index using the proposed model, the five input variables used are the MDD, OMC, LL, $F_{0.08\ mm}$ and $F_{2\ mm}$. The input and output data were normalized by the logarithmic function to obtain good network behavior. 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 of the proposed model gets started with the creation of a random generation composed of a chromosome collection. The size of initial population was considered to be 100. This particular population was then subjected to the genetic operators of selection, crossover, and mutation to produce a new evolved generation. The roulette wheel method was used for the selection operator, whereas for crossover and mutation, probabilities of 0.9 and 0.01 were applied, respectively. A final verification of network performance is made by using the test set. Moreover, the mean absolute error (MAE) is used as a measure of network performance. Four models were developed to predict the CBR_{imm} index. Two hidden layers are considered suitable for good performance. The optimal number of neurons in hidden layers and activation functions is determined using genetic algorithms. The model parameters are summarized in Table 3

Table 3: The parameters of the models developed

Model	Inputs	Topology	Synaptic weights
Model 1	OMC, MDD	2-53-11-1	765
Model 2	LL, OMC, MDD	3-18-44-1	953
Model 3	$F_{0.08mm}$,F_{2mm}, LL, MDD	4-15-12-1	280
Model 4	$F_{0.08\ mm}$,$F_{2\ mm}$, LL, OMC, MDD	5-46-39-1	2149

For all proposed models the genetic algorithm was selected "satlins" as a function of activation of two hidden layers and a linear output. The output of the "satlins" function is obtained as numerical values between -1 and 1. The study shows that the neuro genetic analysis gives a faster convergence compared to the algorithms descended gradient used in a previous work [14]. The correlation coefficient is all in the vicinity of 1 but it does not necessarily mean that the model deduced is adequate because the regression function is an average line linking the output with the input and does not pass through the origin.

Table 4: Comparison between predicted and measured

Measured	Predicted: Model 1	Predicted : Model 2	Predicted : Model 3	Predicted : Model 4
94.20	93.77	97.71	94.61	95.77
94.70	93.77	92.73	92.78	95.40
23.00	17.39	19.52	20.01	23.37
96.50	93.77	95.26	94.91	96.39
90.70	89.87	90.94	93.76	91.64
93.10	93.77	95.71	94.80	94.44
10.00	6.88	13.36	13.25	9.12
90.50	93.77	86.36	89.69	89.71
92.50	93.77	91.31	89.65	93.00
96.00	93.77	92.42	96.30	95.78
5.90	3.87	5.84	11.94	5.91
87.00	93.77	90.40	87.05	88.65
6.00	12.59	11.79	8.71	4.96
R	**0.9910**	**0.9938**	**0.9963**	**0.9996**
MAE	**2.807**	**2.659**	**2.130**	**0.779**
MSE	**12.431**	**9.575**	**6.991**	**0.869**
RMSE	**3.526**	**3.094**	**2.644**	**0.932**
MAPE	**16.989**	**13.071**	**15.906**	**2.797**

The mean absolute error of model 4 which contains five input variable is decreased by 15% compared to model 1 which contains only two inputs which means that using more input parameters in neuro genetic models ensures predictive reliability of the CBR_{imm} index (Table 4).

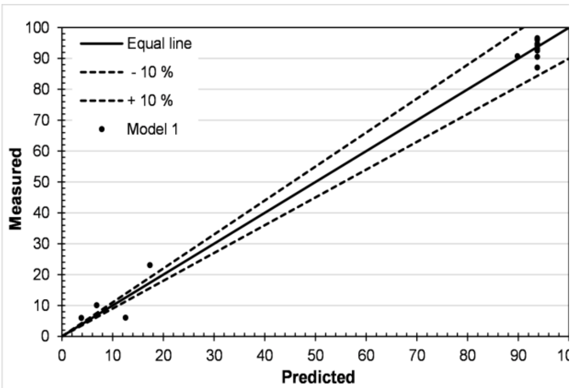


Figure 4.a: Comparison between predicted and measured of model 1

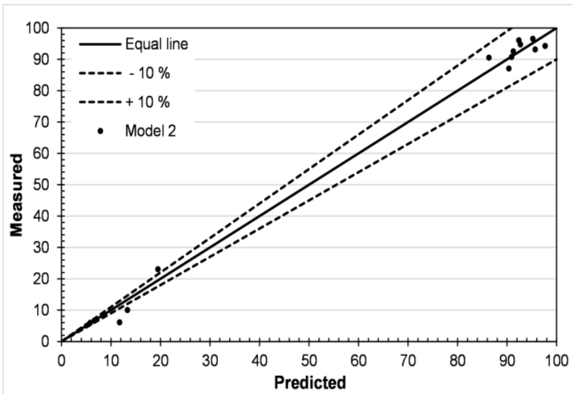


Figure 4.b: Comparison between predicted and measured of model 2

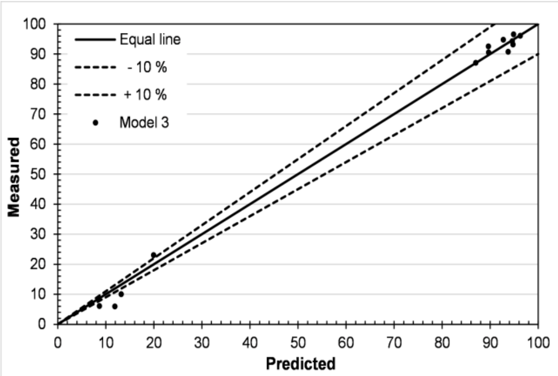


Figure 4.c: Comparison between predicted and measured of model 3

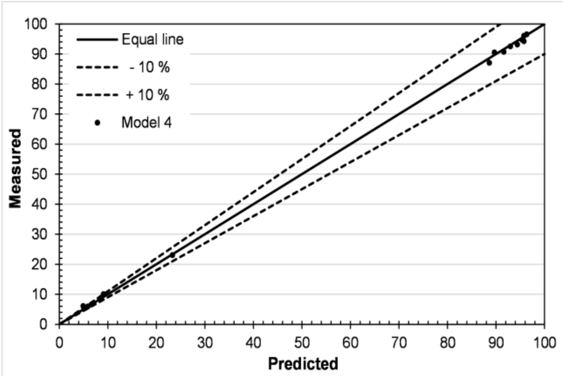


Figure 4.d: Comparison between predicted and measured of model 4

As shown in Figure. 4, model 4 has increased its prediction efficiency with an average absolute error equal to 0.779, all predicted values are included in the error range -10%, + 10%, in contrast to the others models that failed to predict CBR_{imm} index values below 20.

5. CONCLUSIONS

This study was carried out to develop the models of prediction of the CBR index after immersion by exploitation of a database enriched with easily measurable geotechnical parameters. The main conclusions drawn from this study are:

- The choice of two layers hide gave flexibility to our network as it was recommended by Ripley [2].
- The choice of the "stalins" function as an activation function has improved the performance of our network.
- Despite the importance of the number of unknown presented in Table 2 the genetic algorithm has successfully optimized it accurately.
- The use of a large number of parameters makes learning more correct and consequently increases the information available for the networks.
- It is known that the behavior of soils presents a spatial variability, for this it is always preferable to increase the number of influential parameters in the models, which ensures predictive safety.

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