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Estimating the resilient modulus of subgrade materials using visual inspection

Previsão do módulo de resiliência do subleito usando a classificação tátil-visual

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ABSTRACT
The definition of the Resilient Modulus (MR) of subgrade soils is essential for the reliable implementation of mechanistic-empirical pavement design. The MR of the soil is measured through repeated triaxial load tests which require expensive equipment and complex analyses. This reinforces the need to develop accurate statistical models for the prediction of the MR of the subgrade soil to be used for paving highways, especially in developing countries, such as Brazil, where financial resources are limited. The present study used artificial neural networks (ANNs) to create a model for the prediction of the MR of subgrade soils based on a visual-manual classification. For this, the results of MR tests conducted on samples of different soils from northeastern Brazil were used to develop an ANNs model for the prediction of the MR. The results demonstrate that ANNs can predict reliably the MR of soils, with a good degree of correlation in comparison with the laboratory test data. These findings support the use of the ANN model as a cost-effective approach for the preliminary evaluation of subgrade soils for highway pavement design in northeastern Brazil.

RESUMO
A determinação do Módulo de Resiliência (MR) dos solos dos subleitos é essencial para a implementação segura de um método mecanístico-empírico de dimensionamento de pavimentos. O MR de solos é medido por meio de ensaios realizados em equipamentos triaxiais de carga repetida, os quais demandam alto custo de investimento e análises complexas. Diante disso, existe a necessidade do desenvolvimento de modelos estatísticos para a previsão do MR de solos para uso em pavimentação, especialmente em países em desenvolvimento, como o Brasil, onde os recursos financeiros são limitados. Este estudo usou Redes Neurais Artificiais (RNAs) para desenvolver um modelo de predição do MR de solos do subleito, baseado na classificação tátil-visual de solos. Para tanto, os resultados dos ensaios de MR de diferentes solos do nordeste brasileiro foram usados para calibrar os modelos neurais de previsão do MR. Os resultados demonstram que as RNAs podem prever de forma confiável o MR de solos, com um bom grau de correlação, quando comparados aos dados de laboratório. Esses achados sugerem benefícios do uso de modelos neurais como uma abordagem custo-efetiva para a avaliação preliminar de solos de subleito para projetos de pavimentação de rodovias no nordeste do Brasil.

1. INTRODUCTION

In the design of both flexible and rigid pavements, it is important to define the Resilient Modulus (MR) to determine the quality of the materials of the different pavement layers, including the subgrade (Nazzal and Tatari, 2013; Ribeiro, Da Silva and Barroso, 2015). Sadrossadat, Ali and Saeedeh (2016) and Erzin and Turkoz (2016) concluded that the MR is determined primarily by the loading conditions or stress state, and the physical properties of the materials.

The MR can be determined in the laboratory by repeated triaxial load tests, which consist of the application of a repeated deviator stress, with constant cell pressure, to measure the resilient axial strain. The MR (Equation 1) as the ratio between the repeated deviator stress (σ_d) and the recoverable axial strain (εr). In Brazil, this procedure is regulated by the National Transport Department (DNIT) norm 134/2018-ME.

$$MR = \frac{\sigma d}{\varepsilon r} \tag{1}$$

where: M_R: the resilient modulus;

$\sigma_d = \sigma_1 - \sigma_3$: the deviator stress;

σ_1: major stress;

σ_3: confining stress;

εr: recoverable strain.

However, determining the MR in the laboratory is a costly process because it requires a large number of samples, qualified personnel, and in particular, the acquisition of expensive laboratory equipment (Rahim and George, 2005), which is priced at around U$ 150,000 in Brazil. Given this, a number of studies have developed models for the prediction of the MR, based on simple laboratory and field tests, which are processed using statistical procedures and artificial intelligence, such as artificial neural networks. (Patel and Desai, 2010; Zumrawi, 2012; Sadrossadat, Ali and Saeedeh, 2016; Li and Wang 2019; Souza, Ribeiro and Da Silva, 2020).

A number of studies (George, 2004; Kim, 2004; Zeghal and Khogali, 2005; Malla and Joshi, 2007; Archilla, Ooi and Sandefur, 2007; Amiri, Nazarianand and Fernando, 2009; Park *et al*., 2013; Sadrossadat, Ali and Ghorbani, 2018; Tseng and Lytton, 1989; Turk, Logar and Majes, 2001; Gunaydin, Gokoglu and Fener 2010; Alawi and Rajab, 2013; Sabat, 2013; Erzin and Turkoz, 2016; Ribeiro, Da Silva and Barroso, 2018; Tenpe and Patel, 2018) have demonstrated the potential of using soil property indices as explanatory variables to estimate the MR and other geotechnical mechanical characteristics of soils to be used for paving highways. These studies have shown that the value of the MR is affected primarily by the stress states (σ_d and σ_3) and basic soil characteristics, such as the percentage of gravel, sand, and fine substrates (silt and clay), the liquid limit (LL), plasticity index (PI), optimum water content (w_{opt}), and maximum dry density (γ_{dmax}).

Erzin and Turkoz (2016), Zhang and Yu (2016), Ribeiro, Da Silva and Barroso (2018) and Tenpe and Patel (2018) all demonstrated that it is very difficult to define the relationships between the MR and soil properties by linear regression procedures. Given this, artificial intelligence systems, such as Artificial Neural Networks (ANNs), have been widely used to solve statistical questions in pavement and geotechnical engineering (Rakesh *et al.*, 2006; Singh, Zaman and Commuri, 2012; Nazzal and Tatari, 2013; Zhang and Yu, 2016, Sadrossadat, Ali and Ghorbani, 2018; Gong *et al*., 2018).

The Artificial Neural Network (ANN) approach attempts to simulate human brain function in a simplified manner, in a computer system. This approach is based on the use of parallel systems composed of simple processing units (neurons) that calculate specific (nonlinear) mathematical functions. These units are arranged in one or more layers which are interlinked through a large number of connections that are mostly unidirectional (Hecht-Nielsen, 1990; Zurada, 1992; Bredenhann and van de Ven, 2004; Haykin, 2007).

The ANN most used to model parameters for pavement design is the Multilayer Perceptron (MLP) network (see Erzin, Rao and Singh, 2008; Dantas Neto *et al*., 2014; Zhang and Yu, 2016, Ribeiro, Da Silva and Barroso, 2018), which is made up of multiple layers of neurons arranged in three types: the input layer, the hidden layers, and the output layer. The input layer receives the external stimuli, while the hidden layers amplify the capacity of the ANN to capture the behavior of the most complex properties of the phenomenon being modeled, while the output layer presents the responses to the stimuli compiled by the ANN.

The MLP thus consists of multiple layers of neurons that simulate the function of biological neurons (Bayrak, 2005; Nazzal and Tatari, 2013; Sitton, Zeinali and Story, 2017). The inputs are multiplied by a synaptic weight which is, initially, random. These weighted inputs are then added and increased to modify the output of the neuron. The output value is normalized through the application of an activation function. Figure 1 shows a nonlinear mathematical model of an artificial neuron. Neuron k can be described by equations 2, 3 and 4.

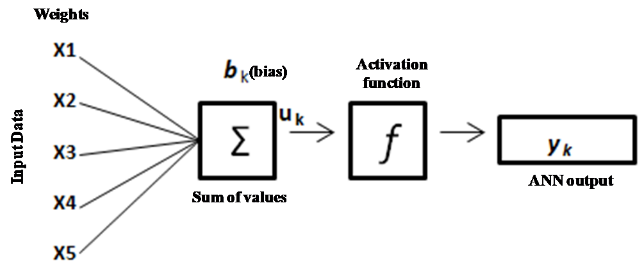

Figure 1. Nonlinear artificial neuron model

$$u_k = \sum_{i=1}^{m} w_{ki} x_i \quad (2)$$

$$v_k = u_k + b_k \quad (3)$$

$$y_k = f_{(v_k)} \quad (4)$$

where: x_i: the ANN input;
w_{ki}: synaptic weights;
b_k: biasterm;
u_k: linear combination of input signals;
$f_{(vk)}$: activation function;
y_k: neuron output.

Bredenhann and van de Ven (2004) used an MLP network to estimate the elastic modulus of flexible pavement layers, while Bayrak, Alperand and Halil (2005) used ANNs to model the resilient behavior of the materials in the layers of flexible pavements in Iowa. Rakesh *et al.* (2006) measured pavement surface deflections using ANNs, the resilient modulus, and the thickness of the layers.

Park, Kweon and Lee (2009) developed a model to estimate the MR of the subgrade and sub-base layer in flexible pavements using ANN to process the associated soil index properties and stress states. Nazzal and Tatari (2013) evaluated the use of genetic algorithms and ANNs to maximize the performance of the predictive models of the subgrade resilient modulus using basic soil properties. Zhang and Yu (2016) used a backpropagation type of model to predict the resilient modulus of the subgrade of highways in Harbin, China.

Similarly, Hanittinan (2007) used ANNs to predict the resilient modulus of three cohesive subgrade soils from Ohio. Johari, Javadi and Habibagahi (2011) combined ANNs and genetic algorithms to model the results of triaxial tests using explanatory data, such as the soil density, axial deformation, the degree of saturation, deviator stress, and the confinement strength. Kim, Yangand and Jeong (2014) used property indices and stress states to estimate the MR of nine different types of subgrade soil in the American state of Georgia using an ANN as modeling tool.

In Brazil, there are few studies to estimate the MR, and the biggest part of it does not have good accuracy to preview this parameter. Thus, the present study evaluated the potential for the prediction of the MR of subgrade soils in northeastern Brazil, based on the visual-manual classification of the soil and ANN. The decision to use a visual-manual classification based on the particle size, and plasticity of the soils was based on the relative simplicity and viability of the data collection procedures, as established by ASTM D2488/2000, and because the literature search identified no studies that have used the visual-manual classification of the properties of the soils applied to pavement area.

2. METHODS

2.1. Database

A total of 1308 datasets collected in northeastern Brazil were used in this study. This database was generated from the previous studies of Benevides (2000), Chaves (2000), Souza Júnior (2006), Bastos (2013), Ribeiro (2016), and Maia (2016).The variables available in this database include the liquid limit (LL), plasticity index (PI), percentage of the soil particles of different sizes (passing through sieves with #1", #3/8", #4, #10, #40, and #200 meshes), the AASHTO classification, maximum dry density (γd_{max}), optimum moisture content (w_{opt}), California Bearing Ratio (CBR), confining stress (σ_3), deviator stress (σ_d), the MR, and the visual-manual classification. The data were obtained using standard Brazilian procedures for the particle size classification (NBR-7181/1984), the Proctor compaction test (NBR 7182/2016), plasticity (NBR-7180/2016), liquid limits (NBR-6459/2016), the determination of the CBR (NBR-9895/2016), and resilient modulus (DNIT134/2018 - ME). The ASTM D2488 (2000) was adopted for the visual-manual classification.

In this paper, the input data for the prediction of the MR were obtained from the laboratory resilient modulus test and the visual-manual classification of the soils. This kind of classification is simplest and determines empirically the texture of the material by inferring the presence of particles of different sizes. Seven variables were selected as the effective parameters for the modeling of the MR of the subgrade soil: gravel, sand, silt, clay, plasticity, confining (σ_3) and deviator stress (σ_d). The input parameters were chosen based on the relative simplicity of the measurement procedures. Rigassi (1985), Minke (2006), Pinto (2006) and Pinheiro (2018), consider the visual-manual identification of soil properties to be a simple, but reliable tool which provides a rapid, preliminary diagnosis of the soil properties without the need for specialized equipment.

2.2. Standardization of the data

As ANN modeling requires quantitative data, the non-numerical datasets were converted to numerical values and standardized, following Rahim and George (2005), Nazzal and Tatari (2013), and Ribeiro, Da Silva and Barroso (2015). For this, the plasticity of the soil was attributed one of three scores: 1 (nonplastic), 2 (poor plasticity), and 3 (plastic). In the case of the grain size fractions, in the case of the grain size fractions, it is necessary for the neural network to differentiate which materials are part of the soil sample (gravel, sand, silt, and clay) and which order of predominance, so that the algorithm has the perception of 100% of the sample. Thus, it was decided to standardize the numerical values of the granulometric fractions as follows, the predominant fraction being scored as 0.60, while the secondary component is assigned a score of 0.20, the third component, a score of 0.15, and the additional component, a score of 0.05. When there are only three components, however, the scores are 0.60, 0.25, and 0.15, respectively, and with two components, they are 0.60 and 0.40. When only one component exists, it is assigned a score of 1 (see Table 1 for examples). This way, in every case, the sum of the fractions was 1, that is, 100%.

Table 1 – Examples of the numeration of the qualitative predictor variables

Visual-manual classification	Numeration				
	Gravel	Sand	Silt	Clay	Plasticity
silty-sandy CLAY with gravel, plastic	0.05	0.15	0.20	0.60	3
silty-gravely SAND, nonplastic	0.15	0.60	0.25	0.00	1
sandy-clayey SILT, low plasticity	0.00	0.25	0.60	0.15	2

2.3. Modeling the Resilient Modulus with ANNs

The artificial neural network tool of Matlab 2015 was used to model the MR. This tool is widely used to model specific phenomena in the field of engineering. One of the most valuable properties of an ANN is its capacity to learn from the examples it is presented with, and thus improve its performance through a process of continuous training. The network is trained by modifying all the existing synaptic weights and thresholds, based on the experience obtained on the phenomenon under analysis. This is typically available in a dataset which contains pairs of known inputs and outputs (Ribeiro, Da Silva and Barroso, 2015; Sadrossadat, Ali and Saeedeh, 2016; Ribeiro, Da Silva e Barroso, 2018).

The majority of the learning algorithms use three types of datasets (the training, validation, and testing datasets) to avoid overfitting. The training and validation datasets are used in the supervised learning phase of the ANN, while the testing dataset is used to test the knowledge level of the network. Once trained, it is possible to use the synaptic weights of the ANN to calculate an output based on novel input data. For this, it is only necessary to apply the weights exported from the model in equations 2, 3, and 4.

In the present study the 1308 datasets were divided randomly into three groups, with 70% of the data vectors being assigned to the training process, 15% being used as validation data (necessary to implement the stop rule of the learning algorithm), and 15% being used to test the models (Haykin, 2007; Ribeiro, Da Silva and Barroso, 2018; Souza, Ribeiro and Da Silva, 2020). Figure 2 shows the sequence of steps in the conventional MR laboratory test and in the procedure proposed here, based on the ANN analysis of the visual-manual classification of the soil. A number of different algorithms with varying parameters (i.e., the number of intermediate layers, the number of neurons per layer, learning rates, the momentum term, and the number of training periods) were also tested.

The Levenberg-Marquardt (LM) algorithm, which is a modified form of the error backpropagation algorithm, was selected to initiate the tests. This algorithm was selected for the initial testing based on the recommendations of Beale *et al.* (2010). The LM algorithm is a function that updates the weights and values of the biases based on their optimization.

This algorithm is widely considered to be one of the most rapid backpropagation training algorithms, although it does require more computer memory than some others (Zhang and Yu, 2016; Ribeiro, Da Silva and Barroso, 2018; Tenpe and Patel, 2018).

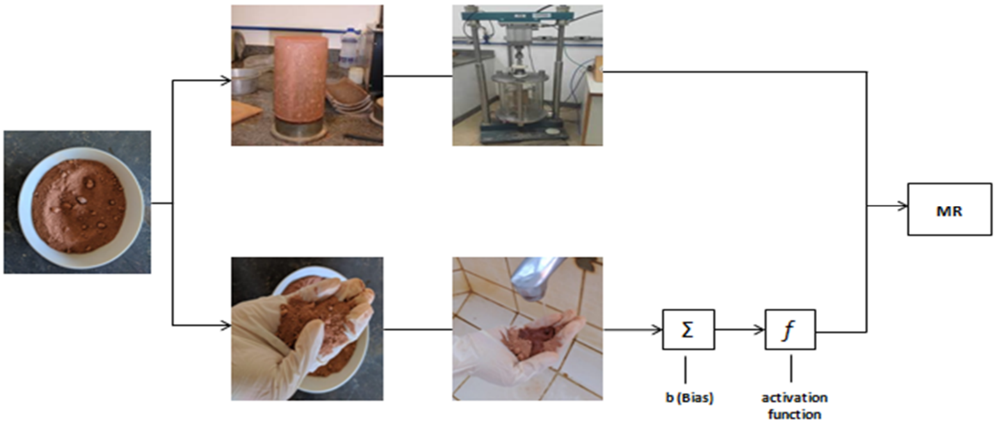

Figure 2. Flowchart of the soil analysis procedures (upper – triaxial load testing, lower – visual-manual soil classification, and Artificial Neural Network)

3. RESULTS AND DISCUSSION

3.1. Overview of the data

These variables were chosed based on the relative simplicity of the data collection procedures, as defined by ASTM D2488/2000. An overview of the variables included in the database is presented in Table 2 with the aim of considering the quality of distributions of variables. Overall, the present study included soils of nine AASHTO classes (A-1-a, A-1-b, A-3, A-2-4, A-2-6, A-4, A-5, A-6, and A-7-5), with 1308 variants of the MR.

Table 2 – Descriptive statistics of the input data

Variable	Mean	Median	Mode	Standard Deviation
Gravel	0.267	0.050	0.050	0.266
Sand	0.392	0.600	0.600	0.214
Silt	0.219	0.200	0.200	0.124
Clay	0.120	0.150	0.150	0.0781
Plasticity	4.568	4.000	0. 000	4.601
σ_3 (MPa)	0.068	0.051	0.051	0.039
σ_d (MPa)	0.137	0.103	0.103	0.102
MR(MPa)	542.38	509.00	635.00	372.91

Haykin (2007) noted that it is important to verify the degree of correlation between the input and output variables of the ANN and concluded that the input variables with a correlation of at least 0.3 tend to be the most efficient for the prediction of the output variables in ANN modeling. The correlations found between the different variables (Table 3) indicate that parameters, such as gravel, sand, clay, σ_3, and σ_d) are the most relevant input variables for the MR prediction, while silt and plasticity have the least predictive potential for the MR.

Haykin (2007) also recommended that variables that have a strong correlation can be combined into a unique value or one of them can be eliminated during the modeling. Rahim and George (2005) notified that for a reliable regression model, the input data should be such that there should not be a strong correlation amongst them. Input variables, if they were highly correlated, would weaken the prediction capability of the model, a problem referred to as multicollinearity. This problem could result in unstable error coefficients and can seriously limit the use of models for inference, such as statistical or artificial intelligence models.

Exploring the correlations between exploratory variables in Table 3, it is possible to note that exist multicollinearity, higher than 0.7, among gravel/sand and σ_3/σ_d. Then, in the modeling process, based on the variable selection criterion (trial and error) to result in the highest possible R and the lowest possible MSE, models were trained in which sand and gravel, and σ_3 and σ_d were not put together as input variables. However, these models did not show good performances when compared to models that used all input data as explanatory variables of the MR.

Table 3 – Correlation matrix of the variables analyzed in the present study

	Gravel	Sand	Silt	Clay	Plasticity	σ_3	σ_d	MR
Gravel	1.000							
Sand	-0.759	1.000						
Silt	-0.420	-0.222	1.000					
Clay	-0.665	0.199	0.456	1.000				
Plasticity	-0.104	-0.046	0.276	0.042	1.000			
σ_3 (MPa)	0.009	0.001	-0.017	-0.008	-0.005	1.000		
σ_d (MPa)	0.013	0.003	-0.025	-0.012	-0.007	0.772	1.000	
M_R (MPa)	0.762	-0.549	-0.321	-0.585	-0.006	0.495	0.528	1.000

3.2. Development of ANN models to predict the MR

The LM algorithm produced the best results for the prediction of the expected MR as the output of the ANN, derived from the processing of the dataset. Beale, Hagan and Demuth (2010), Zhang and Yu (2016), and Tenpe and Patel (2018) recommended the LM as a rapid training algorithm for moderately-sized datasets, as well as having good potential for generalizations, in most cases. The linear coefficient of correlation (R) and the mean squared error (MSE) were used to evaluate the performance of the neural models. Equations 5 and 6 show the performance measures R and MSE, respectively.

$$R = \frac{\sum_{i=1}^{n}(h_i - \bar{h}_i)(t_i - \bar{t}_i)}{\sqrt{\sum_{i=1}^{n}(h_i - \bar{h}_i)^2 \sum_{i=1}^{n}(t_i - \bar{t}_i)^2}} \tag{5}$$

$$MSE = \frac{\sum_{i=1}^{n}(h_i - t_i)^2}{n} \tag{6}$$

where: h_i: observed output values;
t_i: predicted output values;
$\bar{h}_i$: means of the observed outputs;
$\bar{t}_i$: means of the predicted outputs;
n: number of samples.

Approximately 2.000 different topologies were modeled to determine the best MR prediction model, which had a 7:15:1 configuration, consisting of an input layer of seven neurons, an intermediate (hidden) layer of 15 neurons, and an output layer of one neuron. In this model, the intermediate layer was based on an activation function of the sigmoidal tangent type, while the output layer used the identity function.

The number of neurons in the intermediate layer of this model was exactly that indicated by Hecht-Nelson (1987), who recommends having $2i + 1$ neurons in this layer, where i is the number of variables in the input layer. This also corroborates the studies of Hecht-Nelson (1989), Cybenko (1989), and Bounds *et al*. (1988), who all concluded that a single intermediate layer was sufficient to solve a range of engineering problems. Figure 3 shows the architecture of the optimum topology obtained in the present study.

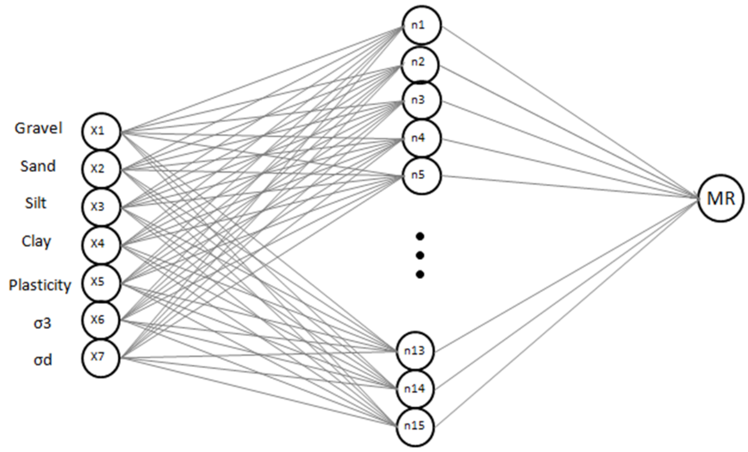

Figure 3. Architecture of the Artificial Neural Network that was most effective for the prediction of the MR

The accuracy of neural models is generally evaluated through the analysis of a test dataset. These ANN outputs are compared with the actual data presented to the ANN only after training and validation. Based on this test analysis, the best-performing model had an R = 0.9597 and an MSE = 0.021. This model was thus considered, statistically, to have the optimal adjustment, as shown in in Figures 4–6, which demonstrate the adjustment of the experimental M_R values to the M_R values obtained by the ANN modeling of the training (Figure 4), validation (Figure 5), and test datasets (Figure 6), with their respective measures of performance (R and MSE).The proximity of the R and MSE values of the training, validation, and test datasets indicate that overfitting was avoided, which implies that the model has good potential for generalization as a procedure for the prediction of the resilient modulus.

The performance coefficients recorded for this model were of the same order of magnitude as those recorded by Rahim (2005), Hanittinan (2007), Kayadelen *et al*. (2009), Nazzal and Tatari (2013) and Tenpe and Patel (2018), which indicates that the input variables selected for this model were sufficient to estimate the MR. This model is not only adequate, but it also avoids the need for costly laboratory testing for the acquisition of the input variables in cases when the financial resources are short, such as in low volume road projects, given that it requires only the data from the visual-manual soil classification.

Pal and Deswal (2014), Sadrossadat, Ali and Saeedeh (2016) and Sadrossadat, Ali and Ghorbani (2018) concluded that the results of statistical analyses are often difficult to understand or interpret. Given theseconclusionsit is interesting to note that the analysis of the residual errors and discrepancies may provide a valuable and precise means to better assess the accuracy and the validity of the model.

Figure 7 shows two curves representing the predicted and experimental MR values for the test dataset ranging from the smallest to the largest. This analysis indicates clearly that the values estimated by the model and those produced in the laboratory follow the same general tendency, albeit with a certain degree of difference. Figure 7 also shows the minimum and maximum discrepancies between measured and predicted MR for the test dataset.

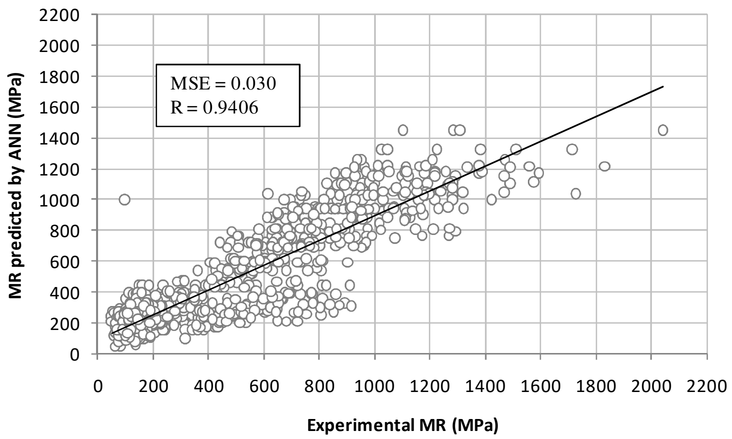

Figure 4. Plot of the predicted *vs.* experimental MR values for the training dataset

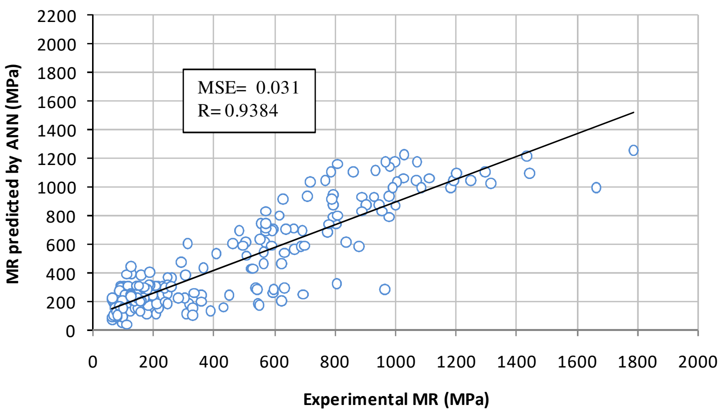

Figure 5. Plot of the predicted *vs.* experimental MR values for the validation dataset

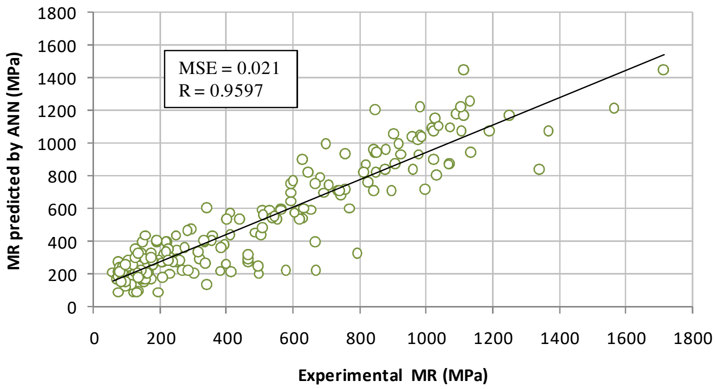

Figure 6. Plot of the predicted *vs.* experimental MR values for the test dataset

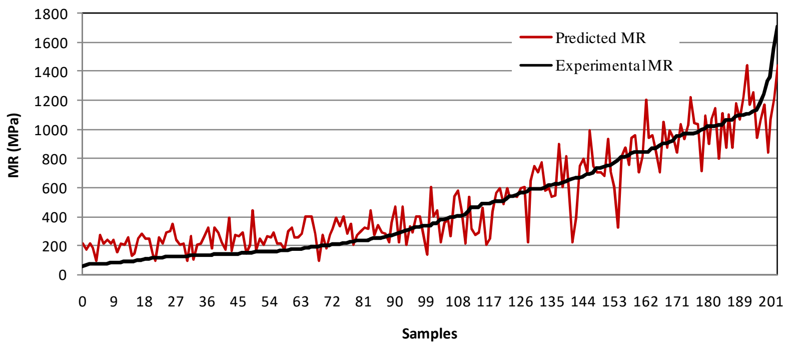

Figure 7. Predicted and experimental MR values for test dataset, organized in ascending order

In order, when evaluating the ability of this neural model to predict the subgrade MR values Figure 7 shows that generally, it has a good tendency of prediction. In addition, it is possible to observe that the values of resilient modulus less than 200 MPa measured in the laboratory are over-predicted and the most part of the laboratory-measured resilient modulus values bigger than 200 MPa are underestimated. However, this model has better correlations for estimating the resilient modulus than those models predict the resilient modulus indirectly from universal constitutive model coefficients (k_1, k_2, and k_3), such as Pezo (1993), and Yau and Von Quintus (2002), both models adopted by NCHRP (2004), where these coefficients are estimated on the basis of basic physical properties of soils.

Table 4 – The weighting and biases of the MR output predicted by the ANN model

Weight from input layer to hidden layer							Bias from input layer to hidden layer	Weight from hidden layer to output layer	Bias from hidden layer to output layer
Gravel	**Sand**	**Silt**	**Clay**	**Plasticity**	**σ_3**	**σ_d**			
0.70	-1.25	-1,06	0.25	1.43	-0.03	-0.90	-2.10	0.41	
-0.52	0.62	1.16	-0.79	0.84	0.74	-0.26	1.80	-0.19	
0.38	0.88	-1.00	-0.01	-0.04	1.08	0.46	-1.80	0.30	
0.41	0.84	-0.59	0.24	-0.07	-0.14	-1.27	-1.10	-0.99	
-0,25	-0.70	1.15	-1.37	0.56	0.20	0.60	0.81	-1.28	
0.81	-0.53	2.09	0.41	0.53	-2.30	-0.20	-0.85	-0.29	
-0.46	-0.67	-0.71	1.92	0.57	0.33	-0.14	0.54	-1.52	
-0.99	-0.65	1.19	0.41	0.08	1.08	0.90	-0.57	0.19	0.31
1.30	0.07	-0.94	1.61	0.31	-0.58	0.38	0.10	-0.77	
-0.51	-0.72	-0.72	1.40	-0.33	-1.19	-0.51	-0.52	-0.24	
-0.53	0.63	-0.75	0.24	0.59	0.11	-2.02	-1.69	1.68	
1.51	-1.79	0.35	0.89	1.42	-0.04	-0.06	1.24	1.27	
-0.82	1.03	-1.09	0.41	0.82	0.33	-2.58	-2.47	-1.04	
-0.59	-0.51	-0.35	1.23	-0.11	-0.62	0.98	-2.09	0.47	
0.35	-0.57	0.46	0.97	-1.29	-0.19	0.00	1.85	-1.06	

These findings indicate that the ANN model developed in the present study can be generalized for the analysis of subgrade soils throughout northeastern Brazil. To enable the implementation of the neural model in future studies, the weights and biases of the intermediate and output layers of the best neural modelare provided in Table 4. Moreover, with these weights, biases, and equations 2, 3, and 4 is possible to calculate the MR for any sample of soil that provides the ASTM visual-manual classification using a spreadsheet.

4. CONCLUSIONS

The models developed in this study obtained a 0.9597 accuracy rate and a value of 0.0212 for the MSE for the for estimating the MR of subgrade soils, based on the topologies composed of seven input variables and an intermediate layer of 15 neurons, with output layer of 1 neurons (7:15:1). In general, the results of the present study indicate that ANN are capable of providing a good estimate of the values of the resilient modulus of subgrade soils, based on data derived from a visual-manual classification.

The model presented here could thus be used to predict the MR of subgrade soils, providing an easily-implemented, cost-effective, and reliable alternative to determine the MR. The input data for this analysis are easily acquired from the visual-manual classification which can help to minimize the time and financial resources required for the preliminary analysis of subgrade soils for highway pavement design when the laboratory tests are not able to be executed, in particular for low-volume roads.

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