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ANALYSIS AND PREDICTION OF THE RESILIENT BEHAVIOR OF SOILS WITH CEMENT ADDITIONS EMPLOYING ARTIFICIAL INTELLIGENCE TECHNIQUES

Stephanny Conceição Farias do Egito Costa
scfecosta@uesc.br
State University of Santa Cruz - UESC, Ilhéus, BA, Brazil.

Adriano Elisio de Figueiredo Lopes Lucena
lucenafb@uol.com.br
Campina Grande Federal University - UFCG, Campina Grande, PB, Brazil.

William de Paiva
wpaiva461@gmail.com
Paraíba State University - UEPB, Campina Grande, PB, Brazil.

ABSTRACT

In Brazil, the development of the mechanistic-empirical method for the design of flexible pavements, MeDiNa, requires parameters related to the mechanical characteristics of materials, including resilient behavior. The resilient strains are obtained in the laboratory with the Triaxial Repeated Load Test, but the equipment necessary for its execution still requires substantial investment capital. Given the evolution of computational modeling and the possibility of acquiring fast and reliable results through intelligent systems, this work aimed to build Artificial Neural Networks capable of predicting the Resilient Modulus of cement-improved soils from their physical characterization. The quality of the models was measured by statistical indexes and an analysis of the differences in the design results using the predicted values compared to those obtained in tests. In addition, statistical analyses were made to verify the change in the properties of the soils studied after adding the binder. The results indicate improvement in the resilient behavior of the materials, but not linearly proportional to the addition of cement. Concerning the prediction of the Resilience Module, good results were obtained for the analyzed indices and, consequently, little or no difference between the dimensioned structures. The Artificial Neural Networks developed in this work showed superior performance compared to those published regarding the magnitude of the prediction errors.

Keywords: Prediction; Resilience Module; Artificial <Neural Networks.

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INTRODUCTION

The mechanistic approach to pavement design had its first contributions in the 1950s from Hveem, who published correlations between loads, deflections, and cracks in asphalt pavements. In the same decade, computational progress expanded research, allowing more refined analyses of the state of stresses and strains acting on the sidewalk.

Nowadays, mechanistic theory occupies a prominent position in the world literature (Han *et al.*, 2018; Khasawneh and Al-Jamal, 2019it is very important to accurately characterize the mechanical behavior of unbound material layers and subgrade soils. In pavement analysis using the elastic layered theory, material properties in terms of dynamic elastic modulus and Poisson's ratio are the major input parameters. The dynamic elastic modulus of pavement materials or resilient modulus (MR; Ren *et al.*, 2019; Haider, Masud, and Chatti, 2020base resilient modulus (MR; Qian *et al.*, 2020; Brizolla de Mello *et al.*, 2021; Chegenizadeh *et al.*, 2022) due to the possibility of analyzing the mechanical behavior of the materials composing the structures closer to reality. Thus, it is evident that there is a global trend to adopt this type of approach in pavement design, given the performance improvements that can be achieved due to a better understanding and modeling of structures.

Given the difficulty in developing and using authentic mechanistic methods, the so-called Mechanistic-Empirical (M-E) approach emerged, using field observations to calibrate the equations relevant to the analyses. Some countries have already adopted the M-E approach for some decades, such as the United States of America, South Africa, and Portugal. The changing trend, added to the limitations of the empirical method (Chiarello *et al.*, 2019; Franco, 2007; Vendrusculo *et al.*, 2018) adopted until then in Brazil, made a new pavement sizing method, MeDiNa (National Sizing Method), emerge in 2018, based on the Multi-Layer Elastic Analysis (MLEA) routine, which allows predicting the pavement's performance regarding fatigue and permanent deformation throughout its service life, enabling the sizing of more durable and safer structures for users.

MeDiNa addresses the deformability analysis of paving structures under traffic loading conditions. In this context, using the Resilience Module (RM) is more appropriate than the method based on the California Bearing Ratio (CBR), which cannot translate the failure mechanisms of flexible pavements because they are associated with the stress state developed by the repetition of loads. The consideration of the resilient behavior of the materials allows for estimating the appearance and intensity of cracks and fissures that cause highway structural deterioration. In addition, MeDiNa admits to using chemically treated materials, highlighting the RM variation between the beginning and end of fatigue service life.

In chemically treated materials, there is the addition of binders that modify soil properties or create a matrix that surrounds or cements the grains. Such a process can occur by adding lime (Andavan and Pagadala, 2019; Cheng et al., 2018; James, 2020), cement (Hataf, Ghadir and Ranjbar, 2018; Solihu, 2020; Ayininuola and Abidoye, 2018), bitumen (Çalisici, 2018; Oluyemi-Ayibiowu, 2019; Dantas Neto, Pereira, and Abreu, 2020) and industry rejects, such as those from rock and mineral processing (Martins and Belchior, 2018), rice husk (Silva, Bello, and Ferreira, 2020), and other possibilities (Miraki et al., 2022; Choobbasti, Samakoosh and Kutanaei, 2019; Hataf, Ghadir, and Ranjbar, 2018).

According to Hanandeh, Ardah, and Abu-Farsakh (2020), there is a difference between chemical stabilization and soil improvement. The small addition of chemicals to dry the soil to the point where the compaction process can be satisfactorily carried out is called enhancement. The addition of products to the point of providing bonds with the soil grains would be stabilization. Despite this difference, both are related to cation exchange capacity and pozzolanic effects. The soil stabilized with cement should meet the density, durability, and resistance requirements, resulting in a hard material with bending stiffness, and the cement content is usually between 6% and 10% in dry weight. For improved soils, the content used is between 2% and 4%, being able to modify the soil concerning plasticity and sensitivity to water and, according to the National Department of Transportation Infrastructure (2006), also allowing consideration of the layer's flexibility.

Despite all the technical gains associated with the development and use of MeDiNa, in practice, obtaining the necessary parameters to feed the calculation routine is a limiting factor, as in the case of RM and Permanent Deformation (PD). The resilient or recoverable strains can be obtained in the laboratory through the Repeated Load Triaxial (RCT) Test; however, the equipment required for its execution requires substantial investment capital because it is too expensive compared to the traditional tests. Moreover, it requires special training for operators and technicians, making its execution on construction sites unfeasible.

In some countries, this obstacle has been minimized by making use of predictive modeling (Zeghal and Khogali, 2005; Solanki, Zaman, and Ebrahimi, 2009; Saha *et al.*, 2018; Khasawneh and Al-jamal, 2019it is very important to accurately characterize the mechanical behavior of unbound material layers and subgrade soils. In pavement analysis using the elastic layered theory, material properties in terms of dynamic elastic modulus and Poisson's ratio

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are the major input parameters. The dynamic elastic modulus of pavement materials or resilient modulus (MR; Farh, Awed, and El-Badawy, 2020) based on Artificial Neural Networks (ANNs), one of the most widely used techniques of Artificial Intelligence, which can identify patterns in large databases and make predictions with a high reliability rate.

In Brazil, Viana (2007), Ribeiro (2016) and Ferreira (2008) used ANNs for predicting RM in soils from the interior of the State of São Paulo, the Metropolitan Region of Fortaleza, and soils distributed throughout the national territory, respectively. In all works, the great potential of using this method was observed; however, in some factors, such as data regionalization in the works of Viana (2007) and Ferreira (2008), the high error values made the use of some developed networks unfeasible, giving rise to the search for refinement and improvement of the results obtained so far.

ANNs are composed of artificial neurons in which each unit is called Perceptron, which, in turn, comprises input signals (data that feed the system), synaptic weights, bias, activation functions, and output. The ANN learning process is the result of sequential adjustments of the synaptic weights until the model responds as close as possible to what is desired. ANNs may present the most varied architectures, i.e., the number of layers and neurons in each. One or more intermediate or hidden layers may be between the input and output layers. When modeling them, the goal is to find the number of intermediate layers, number of neurons, learning algorithms, and transfer functions in each one of them so that the generated results are optimized.

ANN must face training, validation, and test phases to generate the expected result and present it to the data patterns. Routinely, the patterns constituting the database are randomly divided for the mentioned phases, and most of them, approximately 70%, belong to the training set.

The learning process can be unsupervised, reinforced, or supervised. Supervised learning consists of presenting a training set of input patterns and their results to the net. With the validation set, the net can compare the results generated with what is expected and, if necessary, adjust the weights until the output value meets the defined error criteria. The great advantage of supervised learning lies precisely in the possibility of comparing the generated value with the expected one, allowing the accuracy of the outputs to be verified and quality criteria to be established for the model through, for example, the acceptable limits to the measured errors. When the errors reach values considered small, one can admit that the training was sufficient to provide the necessary adjustments.

Given the Brazilian scenario and the development of technologies, the goal was to create prediction models for the RM values of Brazilian soils with small cement additions based on data from the physical characterization of soils, reducing technical and economic limitations relevant to the execution of the TCR test. These predictive models will be built using ANNs, and their quality will be measured by statistical parameters. Their applicability will be tested by comparing the pavement structure design in MeDiNa with the predicted information and the reference information on the resilient behavior of the materials used.

METHOD

Laboratory analysis and statistical treatment

The data used in this research come from tests performed on samples taken from 29 borrow pits used on BR 158/GO and PE 270. Particle size, Atterberg limits, modified energy compaction, CBR, and TCR tests were performed for each sample. The TCR tests were performed at the Pavement Engineering Laboratory of the Federal University of Campina Grande (LEP-UFCG). The others were performed by the companies STS (*Serviços Técnicos de Sondagem*/ Technical Drilling Services) and PDCA Engenharia, following the standards:

- DNER ME 041/94 – Soils - Preparation of samples for characterization tests;
- DNER ME 080/94 – Soils - Sieving granulometric analysis;
- DNER ME 082/94 – Soils - Determination of plasticity limit;
- DNER ME 122/94 – Soils - Determination of liquidity limit;
- DNER ME 129/94 – Soils - Compaction using non-worked samples;
- DNER ME 049/94 – Soils - Determination of California Support Index using unworked samples;
- DNIT ME 134/2018 sendo permitida reprodução parcial ou total, desde que citada a fonte (DNIT– Pavement - Soils - Determination of the resilience modulus.

For the compaction tests CBR and RCT, three test specimen (TS) were molded from each deposit, one of natural soil and two with cement addition, type CP II 32 F - RS by dry weight, at percentages of 2% and 3%, totaling 87 samples for each test. These samples underwent the compaction process soon after wetting. The TSs submitted to the RCT test were stored in a humid chamber for seven days. Given the low levels of cement added, these samples can be called "cement-improved soils," justifying their testing according to the same standard used for natural soils (DNIT ME 134/2018), which allows the practice of tests for "soils and materials improved by small amounts of additions of chemicals or natural fibers (...), provided that they are not chemically stabilized."

After executing the experimental plan, a database was built by compiling the test results plus the TRB classification in an electronic spreadsheet with 22 columns and 1566 rows, each row representing an ANN input pattern. As the data collected for ANN development are of different types, they had to be preprocessed to make them totally numeric. The TRB Consistency and Classification Limits are originally presented in alphanumeric type. Thus, the information referring to the limits was assumed to be "zero" when Non-Liquid (NL) or Non-Plastic (NP). The TRB classification lost the character "A" that begins all nomenclatures and had the "a" and "b" replaced by "1" and "2," and the dash (-) by a comma (,).

After the abovementioned adaptations, the database was submitted to statistical treatment to identify outliers. Points located above and below the respective Upper Limit (UL) and Lower Limit (LL) of the interquartile range (IQR) were considered outliers. These values were analyzed one by one for their exact correction or exclusion, aiming to minimize noise and error generation in the modeling without compromising the quality or size of the database. There was a reduction of 3.45% in the number of input patterns; therefore, the database went from 1566 to 1512 lines (patterns). After this treatment, the data was normalized since they are of different orders of magnitude, and using them in their original form could bias the results.

Analysis of resilient behavior

The analysis of the changes in the resilient behavior of the soils after adding cement contents for their improvement after adding the binder was performed by statistical analysis for each sample studied. The verification, or not, of the statistically significant change in the RM was done through hypothesis tests. These same tests were also used to verify whether the addition of the binder changed the optimum moisture content of the mixtures and whether there was a gain in CBR values.

The first test performed was the Analysis of Variance (ANOVA), which has the independence of observations, normal distribution of sample groups, homogeneity of variances, and absence of outliers as assumptions. These assumptions must be verified and met for correctly applying this type of test. The normality of distribution was examined using the Shapiro-Wilk test, and the homogeneity of variances was analyzed using Levene's test. The results interpreted by analyzing the p-value compared to the adopted significance level (α), which was 0.05 in this research.

After executing the mentioned tests, it was verified if all ANOVA assumptions were met. If so, we proceeded with the Analysis of Variance to confirm whether or not a statistically significant change in the mean RM value occurred. In the case of samples where the assumptions were not met, the non-parametric test corresponding to the one-way ANOVA was performed, in this case, the Kruskal-Wallis test. The conditions for its use refer to the comparison of at least three different and independent samples with six observations that can be ranked. The Kruskal-Wallis test is routinely used when ANOVA cannot be performed to check for equality of parameters between groups. Because it does not require normality in the distributions, it is called a non-parametric test. When this test indicates a difference between at least one group of samples, we proceed with Dunn's test to identify which group is in question.

By performing the tests for the three groups (natural, +2%, and +3%), it was possible to verify whether adding a binder brought about changes in the resilient behavior of the material compared to its natural state.

ANN Modeling

In this stage, ANNs were built to predict the RM based on the results of the geotechnical characterization tests using the MATLAB software. The training was of the supervised type, where the set of expected results is provided together with the input data. The ANNs were composed of three layers (input, hidden, and output). The input layer was made up of 16 variables (cement percentage, percentage passing sieves 50.8 mm (2"), 25.4 mm (1"), 9.5 mm (3/8"), 4.8 mm (no. 4), 2 mm (no. 10), 0.42 mm (#40), and 0.074 mm (#200), LL, LP, TRB classification, optimal moisture, MEASM, CBR, expansion, confining stresses, and deviation), the intermediate had a variable number of neurons, multiples of 4 between 4 and 48, and finally, the output layer had only one neuron, MR.

Feed-forward Backpropagation networks were chosen because they are capable of solving non-linearly separable problems, and three different types of training functions were used, namely: Bayesian regularization (TRAINBR), Levenberg-Marquardt (TRAINLM), and Gradient Descent (TRAINGD). Regarding transfer functions, the possible

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combinations between Linear, Sigmoidal Logistic, and Hyperbolic Tangents were tested. The networks' performance was verified through the values of the Coefficient of Determination (R^2) and Mean Square Error (MSE), electing the network with the best results for RM prediction from these parameters and training time.

Pavement dimensioning

After choosing the best ANN to predict the RM of soils with cement addition, its results were compared to the predicted RM values, calculating the absolute error of each standard. Of the 87 soil samples, the three that presented the highest Mean Absolute Error (MAE) value of the 18 pairs of stresses corresponding to a TCR test were chosen.

The three samples mentioned were used for flexible pavement design using MeDiNa. For comparison purposes, for each structure sized and analyzed with the predicted values, one was sized for the values obtained in the RCT tests.

The dummy structures were sized according to the initial MeDiNa pattern for layers 1, 3, and subgrade. Layer 1 is composed of RJ-type asphalt concrete (AC) CAP 30/45 #12.5mm Sepetiba with 8.8 cm of initial thickness; layer 3 is clay soil LG' (1) with 20 cm; and the subsoil is silty soil NS'. In these layers, there was no change in any physical or mechanical characteristic of the materials. The paving base with a thickness of 20 cm, numbered as layer 2, had an initial thickness fixed at 20 cm; Poisson coefficient, 0.35; Los Angeles Abrasion, 41%; permanent deformation model with regression coefficients $\Psi 1 = 0.1608$, $\Psi 2 = -0.097$, $\Psi 3 = 0.525$, and $\Psi 4 = 0.0752$. The physical characteristics and regression coefficients of the non-linear resilient model were changed according to the material adopted.

As for the traffic data, the MeDiNa default was also used, with the road type being the primary arterial system, average daily volume in the 1st year of 1370, standard single axle double wheel vehicle, design period of ten years, and total N of 5.00×10^6.

The results of the structures modeled with the RM values predicted by the ANN and those determined in the laboratory were compared for final layer thickness, Wheel Track Sinking (ATR), and Cracked Area at the end of the design period.

RESULTS AND DISCUSSION

Laboratory tests

The results of the samples' granulometry and consistency limits allowed classifying the materials according to the TRB, noting that all samples are granular and have excellent to good behavior as subgrade, namely: 17.24% type A-1-a, 20.69% type A-1-b, 55.17% type A-2-4, and only 6.9% type A-2-6. Concerning the group index, all of them presented GI = 0. The percentage of samples passing sieve #50.8 had a value of 100% in all samples, defining it as a constant in the context of this research. This resulted in excluding this variable from all other statistical verifications and its use as input data for the ANNs to be built.

Compaction and CBR tests were performed for all samples (natural, +2%, and +3%) since the added cement contents could cause changes in the optimum moisture content due, for example, to the hydration required for binder activation and an increase in the CBR value due to the possible increase in CP stiffness.

To verify the significance of the change in moisture content in the three test conditions, statistical tests of mean comparison were performed. Initially, it was attempted to proceed with the Analysis of Variance (ANOVA); however, when performing the Shapiro-Wilk test to verify the normality of distribution at a significance level of 5%, it was found that the samples with the addition of 2% and 3% of cement did not have a Normal distribution, violating one of the assumptions necessary to perform the ANOVA and directing the data analysis to non-parametric methods.

The result of the Kruskal-Wallis test indicates that, with 95% certainty, the data tested do not show significant differences. After the tests, it was noticed that the addition of cement in percentages of 2% and 3% did not significantly alter the optimum moisture content of the samples, as was previously expected. It is possible that the amounts used were so small that they did not cause this type of change or that there was not enough time for complete hydration of the binder since compaction occurred immediately after hydration.

The statistical procedure for analyzing the CBR variation was the same as that used for the compaction test results. As for normality, the Shapiro-Wilk test proves its existence for the three sample groups. Levene's test verified the homogeneity of variance among the samples, and the result showed that the variances are not homogeneous for $\alpha = 0.05$. Because the ANOVA assumptions were not met, the

Kruskal-Wallis test was performed, which indicates, with 95% certainty, that there is a difference in at least one sample group. To verify which groups are different from each other, the Dunn test was performed, and it could be verified through a p-value < 0.05 (a condition to reject the null hypothesis) that all groups are different from each other.

According to the tests performed, adding cement to the samples influenced the CBR value, most likely due to the increased stiffness of the TSs due to the hardening of the binder and its effects on the soil matrix. The samples with 2% binder showed an average increase of 39% in the CBR value. The lowest percentage gain in CBR occurred for the samples from deposit 9 of the order of 10%. Still on this same cement content, the quarries 11, 13, 18, 21, 22, and 29 showed an increase in CBR of more than 50%. For adding 3% cement, the average increase in CBR value was 70%, and the samples from quarries 11, 16, 17, 18, 21, and 22 reached more than a 100% increase in CBR value compared to the natural samples.

The expansion results were not analyzed this way since 70% of the samples did not expand.

Resilient behavior

For each of the 87 samples, the RCT tests were performed according to the DNIT 134/2018sendo permitida reprodução parcial ou total, desde que citada a fonte (DNIT-ME. The samples with 2% and 3% cement additions went through the wet curing process for seven days before undergoing the test.

Table 1 presents the averages of the eighteen RM values obtained for each sample and the results of the statistical tests performed to verify the influence of cement addition on the resilient behavior of the samples. The Shapiro-Wilk, Levene, ANOVA, Kruskal-Wallis, and Dunn tests were performed. The Shapiro-Wilk test verifies the normality of each group of samples, so it presents a p-value for each molding condition (natural, +2%, and +3%). The Levene, ANOVA, and Kruskal-Wallis tests generate a single p-value as they analyze the statistical significance of the homogeneity of variances, similarity of means, and populations, respectively. Dunn's test checks for differences between the sample groups, so there is a p-value for each combination (Natural and +2%; Natural and +3%; +2% and +3%). When the conditions for performing an ANOVA were not met, the Kruskal-Wallis test was performed.

Table 1. Mean RM and p-value of the statistical analyses of the TCR test results

	RM (MPa)		
	Nat.	2%	3%
Quarry 1	494	1074	1324
Quarry 2	759	952	1017
Quarry 3	810	1075	936
Quarry 4	736	1248	1280
Quarry 5	428	1118	1386
Quarry 6	453	1019	857
Quarry 7	462	794	1132
Quarry 8	529	1293	1257
Quarry 9	709	1209	1392
Quarry 10	429	1048	1778
Quarry 11	788	1054	1035
Quarry 12	628	818	916
Quarry 13	476	829	760
Quarry 14	637	730	1212
Quarry 15	559	696	1113
Quarry 16	726	781	932
Quarry 17	546	811	883
Quarry 18	550	773	1093
Quarry 19	361	1028	1073
Quarry 20	562	883	1285
Quarry 21	517	775	726
Quarry 22	544	643	644
Quarry 23	401	705	791
Quarry 24	413	841	947
Quarry 25	344	989	1346
Quarry 26	312	845	1320
Quarry 27	463	1377	1658
Quarry 28	433	1616	1787
Quarry 29	420	1563	1497

Source: The authors

The results of the statistical tests indicate that samples 11, 16, and 22 showed no statistical difference, with 95% certainty, between the results of Resilience Modulus for the three test conditions because they presented a p-value for the ANOVA or Kruskal-Wallis test greater than 0.05. For the other samples, knowing that all analyses were performed at the 5% significance level, it was possible to verify the differences between the resilience moduli of the samples by comparing them one by one for each condition of the test specimen. Statistical differences are verified by analyzing the value obtained in Dunn's test. When this value is higher than the adopted significance level, it is inter-

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preted that the groups tend to present equal values of the variable in question. When it is lower, the groups present different values. Thus, we have the following comparisons:

Natural soil and soil + 2% cement: The 2% increment of cement in the natural soil significantly improved the RM values of almost all samples. Only the sample from deposit 15 showed no gains at the 2% content;

Natural soil and soil + 3% cement: The sample with 3% cement from deposit 3 showed no change in resilient behavior compared to the natural soil sample. The other deposits showed significant gains;

Soil + 2% and soil + 3% cement: In only 17% of the samples (quarries 7, 14, 15, 18, and 26), there was a significant difference in RM between the 2% and 3% content. The other samples' results indicate no difference between the addition of 2% or 3% binder, i.e., the addition of 3% cement would increase the service cost without increasing the mechanical benefits in terms of resilient behavior.

Summarizing the analyses of the change in resilient behavior of the materials under study when improved with cement at 2% and 3%, it was found that the addition of the binder had beneficial effects, but that in most cases there was no difference in the gains in resilient behavior when adding 2% or 3%, and it was then more economical to add the 2% binder.

ANN Modeling

Table 2 shows how the net training combinations were created at the time to contain the best-performing net, as will be described later. A total of 648 nets were trained, 216 for each type of training algorithm considered (Bayesian Regularization, Levenberg-Marquardt, and Gradient Descent). The learning algorithms considered were Gradient Descent (LEARNGD) and Gradient Descent with Momentum (LEARNGDM). All nets were created with three layers, so two transfer functions are required: the first between the input and hidden layers and the second between the hidden layer and output layer. This work used all the possible combinations of Linear, Logistic Sigmoidal, and Hyperbolic Tangent transfer functions for each training and learning algorithm.

For each net configuration, architectures with 4, 8, 12, 16, 20, 24, 28, 32, 36, 40, 44, and 48 neurons in the hidden layer were tested, and up to 10,000 training epochs could be reached. The performance of the nets can be measured through processing time, MSE, and R^2.

After modeling all ANNs, the network with the best result was selected based on the highest R^2 values and the lowest MSE value. Of the 100% of input patterns of networks with the Gradient Descent training algorithm, 70% were randomly assigned to training, 15% to validation, and 15% to testing. These networks presented the least satisfactory results, as the highest R^2 value reached was 0.8217 for a network with LEARNGDM, Tangent Sigmoidal, and Linear algorithms and transfer functions, respectively. Regarding errors, the smallest MSE generated was of the order of 10-3. Another characteristic observed for this training set is the small processing time and the range of 10,000 epochs in virtually all nets.

The data set of nets with the Levenberg-Marquerdt training algorithm were divided similarly to those of Gradient Descent and showed better results, as higher R^2 values (0.9840) and lower MSE values (3.32 x 10-4) were observed. Regarding the stopping criteria, none of the nets reached 100 training epochs because this algorithm is programmed to stop if the number of six consecutive failures in the validation phase is reached. This was the main reason for stopping the training of these nets, which occurred most of the time in fractions of a second.

Finally, we have the results of nets built with Bayesian Regularization. This algorithm has the characteristic of removing non-relevant synaptic weights from the training process, and it has its own validation criteria, so there is no need to divide the input data into three phases. In this case, 70% of the data was used for training and 30% for testing. The network number 101 was chosen as the best for presenting the highest R-value and, consequently, R^2 (0.9903), considered an excellent adjustment and one of the lowest MSE (2.77 x 10-4), with LEARNGD learning algorithms and the two Sigmoidal Tangent transfer functions. Its training time was 03:44 minutes for 1069 epochs, with a 16:36:1 architecture. It was found that, of the total number of weights (649) composing the network, 500 were effectively used.

It is assumed that the good performance of the Bayesian Regularization training algorithm was due to its adaptation and generalization characteristics for small databases since the database was composed of only 1512 patterns, a number not considered high for this type of modeling. After training the network, the predicted output values were extracted and transformed to the original order of magnitude since all network inputs and outputs occurred with normed data. This step was necessary to determine the regression coefficients for the Resilience Module Composite Model.

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Table 2. Part of the ANN configurations

				Net No.	Archit.	Epochs	Time	MSE	R	R²
Bayesian Regularization Training	Gradient Descent Learning	Transfer Function (1) Sigmoidal Tangent	Transfer Function (2) Sigmoidal Tangent	93	16:4:1	94	00:00:00	3,86E-03	0.95554	0.913057
				94	16:8:1	302	00:00:03	1,40E-03	0.98314	0.966564
				95	16:12:1	237	00:00:04	9.44E-04	0.98834	0.976816
				96	16:16:1	273	00:00:07	6.14E-04	0.99194	0.983945
				97	16:20:1	333	00:00:12	5.23E-04	0.99302	0.986089
				98	16:24:1	968	00:00:56	4.82E-04	0.99355	0.987142
				99	16:28:1	974	00:02:18	4.22E-04	0.99419	0.988414
				100	16:32:1	702	00:01:33	3.98E-04	0.99406	0.988155
				101	16:36:1	1069	00:03:44	2.77E-04	0.99515	0.990324
				102	16:40:1	2166	00:08:32	3.32E-04	0.99424	0.988513
				103	16:44:1	977	00:05:22	3.15E-04	0.99333	0.986704
				104	16:48:1	2539	00:14:05	2.83E-04	0.99508	0.990184

Source: The authors

Pavement Dimensioning

After transforming the previously normalized RM output data into MPa units, the MAE was calculated between the actual values obtained in laboratory tests and those predicted in the modeling. The objective was to identify the samples that represented the most unfavorable conditions in terms of the predicted RM so that one could evaluate them regarding their sensitivity and possible consequences in pavement design and stress analysis.

It was observed that the higher the MR values, the higher the MAE. Generally, the samples with 3% cement added reached higher MR values compared to those with 2% added and the natural ones due to the order of magnitude of the values. Thus, quarries 9, 20, and 25 contain the samples with the highest MAE, on the order of 100 MPa, all of the soil with 3% cement addition (samples 27, 60, and 75), as shown in Table 3.

Six flexible pavement structures with three layers each were designed. Layers 1 and 3 are the defaults of MeDiNa itself, as well as the traffic data, and the base layer, called layer 2, is composed of the previously mentioned samples. Regarding the adoption of the nonlinear resilient behavior model, three structures were designed based on the test results, and the others were designed based on the results obtained from predictions with the chosen ANN. The physical characteristics of layer 2 were also defined from laboratory tests of the samples. The Poisson coefficient and the Permanent Deformation model were adopted for the Graded Gravel - Gneiss C1 from the MeDiNa database.

The regression coefficients k1, k2, and k3 of the Composite Model and R^2 for the tested and predicted RM values of each sample and the cracked area for the end-of-period, total Roadway Rutting (ATR), and final thickness of each layer are presented in Table 4. Regarding the regression coefficients, it can be seen that all the values of k1 and k2 are positive, indicating the increase in RM as a function of the confining stress and that the k3 values were negative for samples 60 and 75, leading to less influence of the deviation stress in their behavior. The k_1 reached higher values for the modeling situation using the predicted values. Sample 27 was the most affected, with a difference of approximately 16% compared to the value model with the test data. The opposite behavior occurred for k_2, in which the predicted values resulted in lower values of this coefficient. Except for sample 27, for k_3, the other values were very close.

For the paving design, changing only the resilient model parameters of the base course and fixing the fatigue and permanent deformation models of all materials, it was noticed that there was a 3.3% and 0.2 mm reduction of the cracked area at the end of the design period and ATR, respectively, for sample 27 and 2.7% and 0.1 mm for samples 60 and 75 for using the predicted data compared to the real ones. The reductions presented did not lead to changes in the thickness of the layers of the structure for samples 27 and 75. Only sample 60 presented a reduction of 1 cm in the thickness of the asphalt concrete.

CONCLUSIONS

The results showed that adding low cement contents to natural soils can bring gains regarding the improvement of resilient behavior; however, there is no direct relationship between the increase in content and the RM values. In this

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Table 3. Highest Sample Absolute Mean Error

Confinement Stress (MPa)	Deviation Stress (MPa)	Sample 27		Sample 60		Sample 75	
		Real RM (MPa)	Predicted RM (MPa)	Real RM (MPa)	Predicted RM (MPa)	Real RM (MPa)	Predicted RM (MPa)
0.020	0.020	746	848	589	660	967	1028
0.020	0.040	838	793	516	629	859	894
0.020	0.060	614	768	668	639	707	827
0.035	0.035	1042	1111	855	866	984	1226
0.035	0.070	954	1036	784	874	978	1065
0.035	0.105	976	1030	940	976	1018	1032
0.050	0.050	1242	1372	1077	1225	1665	1649
0.050	0.100	1189	1302	1080	1224	1246	1429
0.050	0.150	1231	1348	1140	1315	1197	1324
0.070	0.070	1487	1589	1540	1655	1718	1858
0.070	0.140	1387	1545	1434	1517	1359	1565
0.070	0.210	1508	1640	1349	1488	1280	1390
0.105	0.105	1765	1978	1838	2050	1846	2007
0.105	0.210	1902	2025	1694	1903	1638	1759
0.105	0.315	1868	2090	1727	1870	1513	1656
0.140	0.140	2084	2262	2117	2260	1918	2156
0.140	0.280	2118	2278	2005	2185	1792	1951
0.140	0.420	2075	2270	1773	1953	1549	1705
MAE		131		129		123	

Source: The authors

Table 4. Regression Coefficients and Pavement Design Results

	Sample 27		Sample 60		Sample 75	
	Tested	**Predicted**	**Tested**	**Predicted**	**Tested**	**Predicted**
k1	6311.95	7350.75	7027.03	7434.74	4334.27	4691.48
k2	0.5512	0.5174	0.6854	0.6643	0.5853	0.5771
k3	0.0033	0.0686	-0.0782	-0.0712	-0.2052	-0.2026
R^2	0.9854	0.9743	0.9678	0.9722	0.9227	0.9625
Cracked area (%)	23.9	20.6	29.1	26.4	26.3	23.6
Total ATR (mm)	5.2	5	5.3	5.2	5.3	5.2
Thickness layer 1 (cm)	5	5	6	5	5	5
Thickness layer 2 (cm)	20	20	20	20	20	20
Thickness layer 3 (cm)	20	20	20	20	20	20

Source: The authors

study, the addition of 3% of cement CP II 32 F - RS to the soils studied did not exceed the gains for resilient behavior compared to those with a 2% addition.

Regarding the prediction of RM values using ANNs, good results were observed in the developed modeling, with high R^2 values (above 0.99) concomitant with low MSE values (around 10-4). Despite the quality of these statistical indexes, there were differences in the estimates of cracked area and ATR in the paving design. The structures dimensioned with the predicted values undersized these parameters; despite this, only one of the samples showed a difference of 1 cm in the thickness of the asphalt concrete layers.

The results indicate the great potential of using ANNs to predict the soil's resilient behavior. Given the countless architectural possibilities, transfer functions, and learning algorithms, in addition to the possibility of verifying the quality of the networks by other statistical quality indicators and the increase in the database, it is possible to obtain results that are closer to the real ones and, consequently, similar to the final design of the pavements.

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