Abstract: Accurately forecast performance and durability is a critical issue for improving the design of new and existing pavements. The poor pavement performance increases traffic congestion, compromises safety, and raises maintenance costs due to frequent repairs. The resilient modulus is one of the most critical unbound material property inputs in several current pavement design procedures. Recent studies have addressed the problem of resilient modulus prediction using different methods, including computational intelligence approaches. In this paper, a hybrid intelligent system called ANFIS (Adaptive Neuro-Fuzzy Inference System) is used for predicting the resilient modulus from an experimental database of 270 distinct compositions. ANFIS achieved superior performance when estimating the resilient modulus of bituminous mixes, which can potentially save laboratory resources.

Keywords: Bituminous mixes. Resilient modulus. ANFIS
**Resumo:** Prever com precisão o desempenho e a durabilidade é uma questão crítica para melhorar o projeto de pavimentos novos e existentes. O baixo desempenho do pavimento aumenta o congestionamento do tráfego, compromete a segurança e aumenta os custos de manutenção devido a reparos frequentes. O módulo resiliente é uma das entradas mais importantes de propriedades de materiais em vários procedimentos atuais de projeto de pavimentos. Estudos recentes abordaram o problema da previsão de módulo resiliente usando diferentes métodos, incluindo abordagens de inteligência computacional. Neste artigo, um sistema inteligente híbrido chamado ANFIS (Sistema de Inferência Adaptativa Neuro-Difusa) é usado para prever o módulo resiliente de um banco de dados experimental de 270 composições distintas. O ANFIS obteve bom desempenho ao estimar o módulo resiliente de misturas betuminosas, o que pode potencialmente ajudar a economizar recursos de laboratório.

**Palavras-chave:** Misturas betuminosas. Módulo resiliente. ANFIS.
1 INTRODUCTION

The structure of a pavement consists of the subbase, the base course, and the surface course. The surface course or surface layer is the layer of a pavement structure designed to accommodate the traffic load. The surface course resists skidding, traffic abrasion, and the disintegrating effects of climate. The surface layer may consist of asphalt (also called bituminous) concrete, resulting in a so-called flexible pavement, or Portland cement concrete, classified as rigid pavement. The elastic modulus for pavement materials is most commonly characterized in the resilient modulus (MR). MR has been recognized as an important property that governs the subgrade and granular materials performance (AASHTO, 1986; AUSTROADS, 2012) and has been recommended for pavement design and analysis. Determined directly from dynamic tests, MR is one of the main mechanical properties of asphalt mixes. This modulus is defined as the ratio of the applied cyclic stress to the recoverable (elastic) strain after many cycles of repeated loading and thus is a direct measure of stiffness for unbound materials in pavement systems (AASHTO, 1986). The resilient modulus is used in the design of asphalt pavements to compute stresses, strains, and deformations induced in the pavement structure by the applied traffic loads (FAKHRI; GHANIZADEH, 2014). MR is influenced by several parameters related to the type of bituminous mix, the amount and particle size of the aggregate, content, type of binder asphalt, the building technique, and the degree of compaction adopted in the preparation of the material. In addition to the stress level, MR can also be affected by other soil parameters, such as moisture content, especially for fine-grained soils. Change in the moisture content can quickly happen to the pavement during the construction stage and in the long term (NGUYEN; MOHAJERANI, 2016). Besides, the temperature is an important parameter, since it can change the viscosity of the mix and may considerably affect its compactibility.

The protocols for resilient modulus testing in the laboratory usually involve repeated analyzes resulting in time-consuming tasks. An interesting alternative relies on machine learning tools as surrogate models to expensive laboratory tests. In the last decades, Computational Intelligence techniques such as Neural Networks (NN), Support Vector Machines, Genetic Programming (GP), and Fuzzy Inference Systems (FIS) have been explored to predict outcomes of interest in real-world engineering problems. The Adaptive Neuro-Fuzzy Inference Systems (ANFIS), which combines the adaptive behavior of neural networks and the flexibility of fuzzy Inference Systems, is a powerful and accurate technique to deal with regression or approximation problems and arises as an alternative to predict the mechanical properties of pavements.

Despite the recent advances in the Computational Intelligence approaches, there are few
attempts in the literature to predict the MR of bituminous mixes. A Neural Network was implemented in (OZSAHIN; ORUC, 2008) to predict the resilient modulus of emulsified asphalt mixtures. In (YILMAZ et al., 2011) was developed a model to predict the complex modulus of base and ethylene-vinyl acetate (EVA) modified bitumen using ANFIS. A prediction model based on the ANFIS was developed to predict the stiffness modulus of asphalt core samples in (ÖZGAN; KORKMAZ; EMIROĞLU, 2012). In Reference (MAZARI et al., 2014), the authors developed a nonlinear numerical structural model and compared numerical and experimental responses of pavement systems using various resilient modulus models. Some authors explored the effects of loading features on resilient modulus of asphalt mixtures using ANFIS in (SHAFABAKHSH; TANAKIZADEH, 2015). An adaptive neuro-fuzzy methodology was used in (POURTAHMASB; KARIM; SHAMSHIRBAND, 2015) for resilient modulus prediction of asphalt mixtures containing Recycled Concrete Aggregate. The potential of an adaptive neuro-fuzzy inference system was investigated in (SADROSSADAT; HEIDARIPANAH; OSOULI, 2016) for the prediction of resilient modulus of flexible pavements subgrade soils.

This paper’s objective is to evaluate the performance of the ANFIS to predict the resilient modulus of dense asphalt mixes designed according to the Brazilian Standard DNIT 135/2010 (DNIT, 2010). The mechanical properties of these mixes have been evaluated to build a comprehensive database and assess the effect of the constituents when working temperatures decreased. The computational methodology can potentially replace unnecessary, destructive tests, guiding the experiments to the more rational use of the materials, which helps save laboratory resources.

The remainder of this paper is organized as follows. Section 2 presents the experimental database and describes the formulation and the parameters of the Adaptive Neuro-Fuzzy Inference System used in this paper. Besides, this section explains the computational procedure employed to obtain the results and the statistical measures used to assess its performance. The computational experiments and the results are presented and discussed in Section 3. Section 4 provides the conclusions and directions for future work.

2 MATERIALS AND METHODS

This section presents the main concepts in the framework of this paper. The section starts with a brief explanation of the experimental dataset and its statistical description and the range of each descriptive variable. After, the architecture of the ANFIS framework is explained in detail. The cross-validation technique used to conduct computational experiments is also presented. Finally, the performance metrics used to evaluate the results are described.
2.1 Experimental Database

The data were collected from dynamic tests using distinct mixtures, according to the Brazilian Standard DNIT 135/2010 (DNIT, 2010). This database was obtained from the Federal University of Juiz de Fora, and it is composed of 270 test samples, four input parameters (viscosity, temperature, asphalt binder content, and aggregate granulometric properties) and the resilient modulus as output (MARQUES, 2004). For each sample, three measurements of MR value were performed, and the arithmetic mean of these measurements was used as output. Marshall cylindrical samples were prepared using different modified binders and the aggregate gradation corresponding to bituminous concrete. Table 1 shows the input variables used in the experimental dataset and their respective values.

| Input or output parameter | Levels | Values |
|---------------------------|--------|--------|
| Viscosity (P)             | 3      | 3144, 4440, 4367 |
| Air voids (%)             | 90     | Measured experimentally |
| Asphalt binder content (%)| 5      | 3.5, 4.5, 5.5, 5.0, 6.0 |
| Temperature (°C)          | 3      | 10, 25, 35 |

2.2 Adaptive Network Fuzzy Inference System – ANFIS

The ANFIS model, introduced in (JANG, 1993), is a combination of an adaptive network and a fuzzy inference system. The ANFIS constructs an input-output fuzzy inference model according to both the fuzzy if-then rules and the stipulated input-output data pairs (REDDY; MOHANTA, 2007). The if-then rules of the fuzzy system are usually employed to obtain the inference of an imprecise model, which can process information in a system as well as human experience. It is a class of adaptive, multi-layer, and feed-forward networks. Because of these minimal restrictions, ANFIS can be directly employed in a wide variety of modeling applications where uncertainties are present.

For simplification, it is assumed that the framework of ANFIS has two inputs \( x, y \), and one output \( z \). The corresponding rule set with two fuzzy if-then rules for a fuzzy model can be expressed as (AKKAYA, 2016):

- Rule 1: If \( x \) is \( A_1 \) and \( y \) is \( B_1 \) then \( z_1 = p_1 x + p_1 y + r_1 \)
- Rule 2: If \( x \) is \( A_2 \) and \( y \) is \( B_2 \) then \( z_2 = p_2 x + q_2 y + r_2 \)
Entries are evaluated by linguistic variables \((A_i, B_i)\). A linear combination of the input values with a constant term \(r\) is used to obtain each rule result. A linguistic variable corresponds to a linguistic concept. For example, \(A\) and \(B\) can be linguistic labels such as “low” and “high”. During the reasoning procedure the fuzzy sets determine the correspondence with the numerical values characterized by different membership functions such as generalized bell, sigmoid or triangular.

Figure 1: Architecture of an Adaptive Network-based Fuzzy Inference System which contains five layers with two inputs and one output (AKKAYA, 2016).

Figure 1 shows a simplified diagram of ANFIS architecture. In the following, each layer function in ANFIS is described.

- **Layer 1:** The main purpose of Layer 1 is to map input variables \((x\) and \(y)\) into fuzzy sets \(S = \{A_1, A_2, B_1, B_2\}\) through the process of fuzzification. Each node in this layer is a square node with node functions which outputs are the membership grades \(\mu\). In this paper, tests were performed with two, three and four gaussian membership functions given mathematically by

\[
\mu(t) = \exp \left[ - \left( \frac{t - c}{a} \right)^2 \right], \quad t = x, y, \tag{1}
\]

where \(a\) and \(c\) are the nonlinear parameters of the membership function.

- **Layer 2:** In this layer, firing strength will be used after combining the fuzzy sets of each input. The \(\prod\)-norm operator performing the fuzzy conjunction (“and”), is used to obtain the output.

\[
w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1, 2. \tag{2}
\]
• Layer 3: Every node in this layer is a fixed node labeled \( N \). The \( i \)th node calculates the ratio of the \( i \)th rule’s firing strength to the sum of all rules’ firing strengths:

\[
\bar{w}_i = \frac{w_i}{\sum w_i}, \quad i = 1, 2.
\]

(3)

• Layer 4: In this layer, the output from the previous layer is multiplied with an adaptive node with a node function

\[
\bar{w}_i z_i = \bar{w}_i (p_i x + q_i y + r_i), \quad i = 1, 2,
\]

where \( \bar{w}_i \) is output of Layer 3, and \( p_i, q_i, \) and \( r_i \) are the parameter set of this node. The node parameters are determined during the learning procedure, which will be explained below.

• Layer 5: There is only one node in this layer, a fixed node labeled \( \sum \), which computes the overall output as the summation of all incoming signals as

\[
z = \sum_{i=1}^{2} \bar{w}_i z_i.
\]

(5)

The parameters in the ANFIS architectures \((a, c, p_i, q_i, r_i)\) were determined using a hybrid learning algorithm. The learning procedure requires an iterative loop. Each iteration denotes an epoch and the dataset is used in the network learning. To minimize the error between the desired and the real output, there is an adjustment of the weights by means two steps: forward and backward. In the forward pass of this algorithm, functional signals go forward until Layer 4. The parameters \( \bar{w}_i \) are identified by the least squares estimate. In the backward pass, the error rates propagate backwards. The variables in the first layer parameters are updated by the gradient descent (POURTAHMASB; KARIM; SHAMSHIRBAND, 2015).

In this paper, viscosity \((P)\), air voids \(\%\), asphalt binder \(\%\) and temperature \(\circ\) were parameters chosen as the input layer, and the resilient modulus (MPa) of asphalt mixes was chosen as the output layer. This structure is illustrated in Fig. 2.

2.3 Cross-Validation

Aiming at assessing the prediction ability of a method, it is necessary to use a statistical technique for generalization, so it is possible to assure the method can also succeed precisely when estimating independent data. The cross-validation is a classical statistical technique that makes it useful to determine the models’ generalization. For this, the database should be divided...
into two distinct sets: (i) training set, used in order to make the neural network learn and fit the necessary parameters (ii) validation set: used to test or validate the trained network.

After training the neural network for a predefined number of times (in this paper were used eight times), the training is interrupted, and the network is tested with the validation data. The process is repeated until the network performance stabilizes at a value considered acceptable for the problem. The motivation for this split is to validate the model in a different set of data used to adjust the ANFIS parameters and, therefore, it also avoids occurring the phenomenon called over-training. When over-training occurs, the neural network strongly learns the training data and cannot generalize this knowledge for new unseen data.

There are several methods in the literature to carry out the cross-validation technique. For this work, we chose the K-fold. The procedure requires that the original training set is divided randomly into K subsets. For each database, K subsets are obtained in the division, and one is separated to validate the model already trained in the (K – 1) other subsets. The procedure is then repeated K times for the trained model so that all K subsets are used exactly once as test data for validation of the model. In this work, we choose K = 10, as shown in Fig 3.

2.4 Performance Metrics

In order to evaluate the prediction models performance were used in this study four metrics: the $R^2$ coefficient of determination; MAPE (Mean Absolute Percentage Error); MSE (Mean Squared error); and RMSE (Root Mean Square error). For all formulas presented below we have $O_i$, $i = 1, \ldots, N$ as the observed values, $Y_i$ as the predicted values, $\bar{O}$ is the average of $O$ and $N$ is the total number of observations.
The coefficient of determination, denoted $R^2$ ranging from 0 to 1, is a number that indicates the proportion of the variance in the dependent variable that is predictable from the independent variable. Higher values mean the model better explains the experimental data. Its value is given by:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (O_i - Y_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2}.$$  

(6)

MAPE is also a measure of prediction accuracy and it usually expresses accuracy as a percentage, and is defined by the formula:

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \left| \frac{O_i - Y_i}{O_i} \right|.$$  

(7)

Finally, RMSE measures the root mean square error or deviations, the difference between the estimator and what is estimated. RMSE is associated to the risk function, corresponding to the expected value of the squared error loss or quadratic loss. It is always non-negative, and values closer to zero are better.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (O_i - Y_i)^2}.$$  

(8)
3 RESULTS AND DISCUSSION

In this section, the results obtained are presented and discussed. In all computational experiments, we have used 10-fold cross-validation, and in order to obtain consistent and reliable metrics, a total of 30 runs were executed with different random seeds in each one. In the ANFIS training procedure, the total number of epochs was set to 100. In each run, the dataset is shuffled to assure different folds in cross-validation. The number of the membership functions tested for each input variable was two, three, and four.

The number of membership functions, denoted by $N_F$, is an important parameter in building the ANFIS architecture. To investigate the effects of the number of membership functions in modelling the $M_R$ values, a total of 30 independent runs were performed with distinct training and test datasets using the 10-fold cross-validation. Figure 4 shows the boxplots for the prediction obtained using the ANFIS approach according to the number of membership functions. To compare the performance of ANFIS for different $N_F$ values, three metrics described in the last section were considered. From Fig. 4, one can observe that $N_F = 2$ produced higher values for $R^2$ and smaller MAPE and RMSE when compared to $N_F = 3$ and $N_F = 4$. These results show that increasing the number of membership functions per input does not necessarily increase model performance according to MAPE, RMSE and $R^2$. Considering the computational and numerical aspects, increasing the number of membership functions also increases the number of parameters to be learned, which makes the minimization task involved in the parameter determination harder. This scenario can potentially lead to suboptimal solutions resulting in a model with worse performance.

The statistical parameters obtained during the computational experiments are summarized in Table 2. The first column shows the number of membership functions, the second one displays the $R^2$ coefficient while MAPE and RMSE appear in the third and fourth columns, respectively. All entries are averaged in 30 independent runs and the standard deviations are shown in parentheses. The boldface values indicate the best results. As can be seen in Figure 4, $N_F = 2$ leads to consistently better results for MAPE, RMSE and $R^2$.

The predicted and experimental values of $M_R$ obtained by the best model are illustrated in scatter graph of Figure 5. In this graph it is possible to identify the relationship between real and predicted data, where the red line represents the perfect linear correlation between the data.

The statistical metrics used in this paper are important performance parameters of fit of the ANFIS model. However, they are not usually easily comprehensible and can become hard to interpret. An interesting way to observe the lack of match of the predicted and experimental values is to consider the errors and Confidence Interval (CI) between observed and predicted
Figure 4: Comparison of the influence of the number of membership functions to the performance metrics MAPE, RMSE and $R^2$ (averaged in 30 independent runs).

Table 2: MAPE, MSE, $R^2$ and their respective standard deviations within parentheses in predicting $M_R$ values.

| # of MF | $R^2$   | MAPE    | RMSE    |
|---------|---------|---------|---------|
| 2       | 0.806 (0.057) | 24.660 (2.085) | 1912.83 (246.65) |
| 3       | 0.778 (0.089) | 26.562 (3.485) | 2040.10 (328.38) |
| 4       | 0.767 (0.048) | 27.381 (2.729) | 2102.34 (214.03) |

values. Figure 6 shows the prediction of the best model using 2 member functions and its respective performance metrics. The MR values are sorted from the smallest to the largest and the 95% level of confidence for all samples are depicted. In this Figure, one can observe the difference of a specific value and compare whether the predicted values appear out of the CI of the experimental values.
Figure 5: Predicted versus experimental MR values using selected ANFIS model for the best model found in 30 independent runs.

ANFIS: $MAPE = 22.154\%$ - $R^2 = 0.842$

$RMSE = 1743.378$, $N_F = 2$

Figure 6: Results produced by the best ANFIS model, which used two membership functions and produced the best values for $R^2 = 0.842$ and MAPE equals to $22.154\%$. This figure shows the observations and the predictions inside and outside the 95% confidence interval for each sample.

4 CONCLUSIONS

Through the presented results, it is possible to see that the Neuro-Fuzzy ANFIS system can accurately estimate the resilient modulus, obtaining small error values and standard deviation. Considering the MAPE, RMSE and $R^2$, ANFIS achieved better predicting when
using only two membership functions. The results show the robustness of the ANFIS approach for estimating MR of bituminous mixes, which can potentially help save laboratory resources. Despite the performance of the ANFIS in the present paper, the data-dependent nature of computational intelligence-based modeling approaches is a major issue. Their outputs depend on the dataset, data scaling procedures, and user-defined parameters, thus requiring more studies to establish the usefulness of ANFIS and the usefulness of other computational intelligence techniques as an alternative modeling tool.

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